EUFAR Training Course

Airborne Remote Sensing for Monitoring Essential Biodiversity Variables in Forest Ecosystems (RS4forestEBV)

Bavarian Forest National Park and German Aerospace Center, Germany,

3-14 July 2017

Lecture 11: Tree Species Classification

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UNIVERSITY OF TWENTE.

Deutsches Zentrum für Luft- und Raumfahrt

NATIONALPARK Bayerischer Wald

NERC SCIENCE OF THE ENVIRONMENT

vito vision on technology

METEO FRANCE

Tree species information

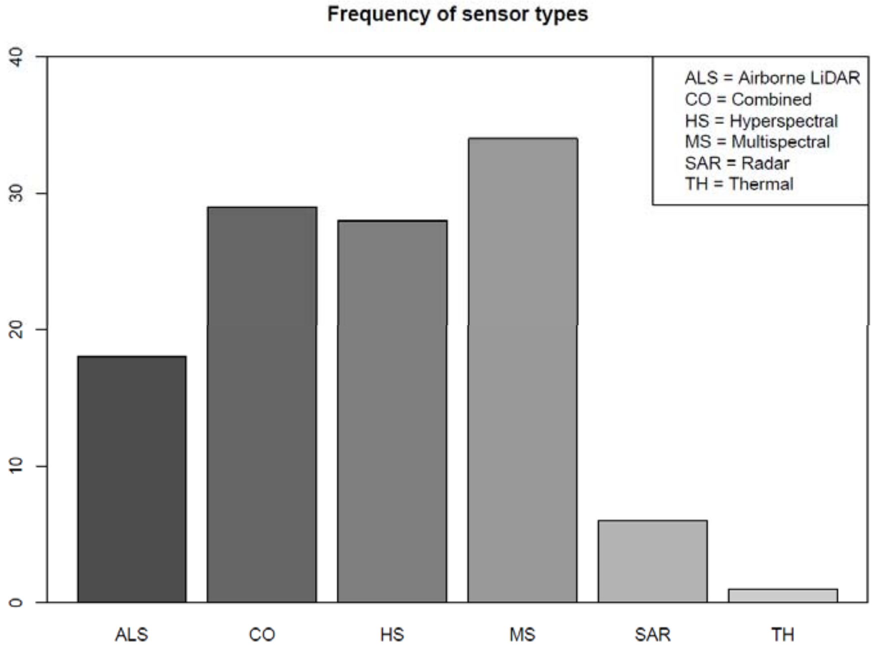
Motivation by a wide variety of applications confronting the forest management and conservation sector:

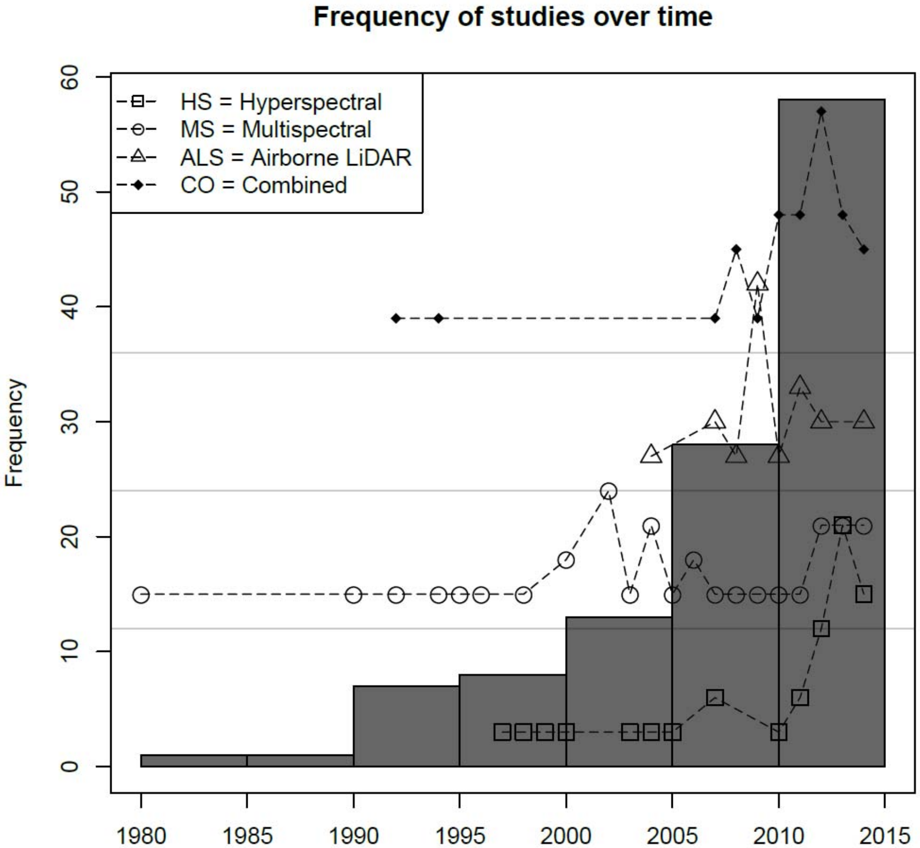
- Resources inventories
- Biodiversity assessment
- Hazard and stress management
- Monitoring invasive species
- Wildlife habitat mapping
- Sustainable forest management

Objective

- General trends in remote sensing studies focusing on tree species classification
- Provide an overview of the current approaches for classifying tree species
- Indentify research gaps and future trends for tree species classification using remote sensing data
- Case study: Bavarian Forest National Park

Overview





Descriptive statistics compiled from 116 selected studies focusing on tree species mapping

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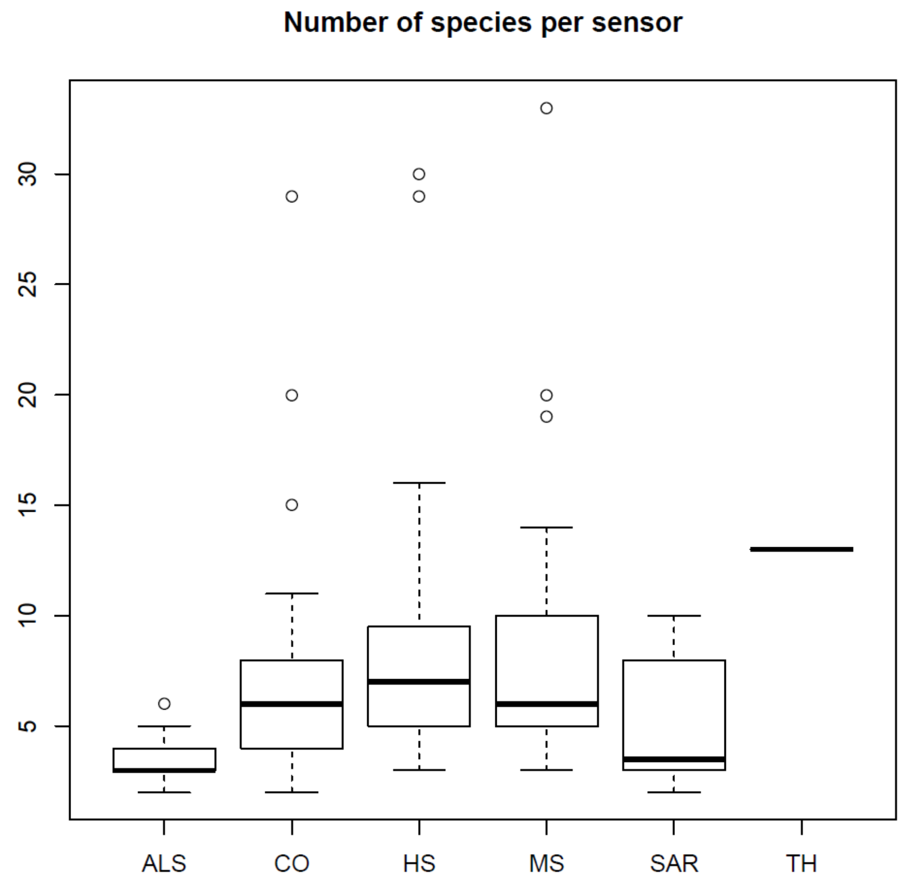
Overview

Number of species per sensor type.

Descriptive statistics compiled from 116 selected studies focusing on tree species mapping



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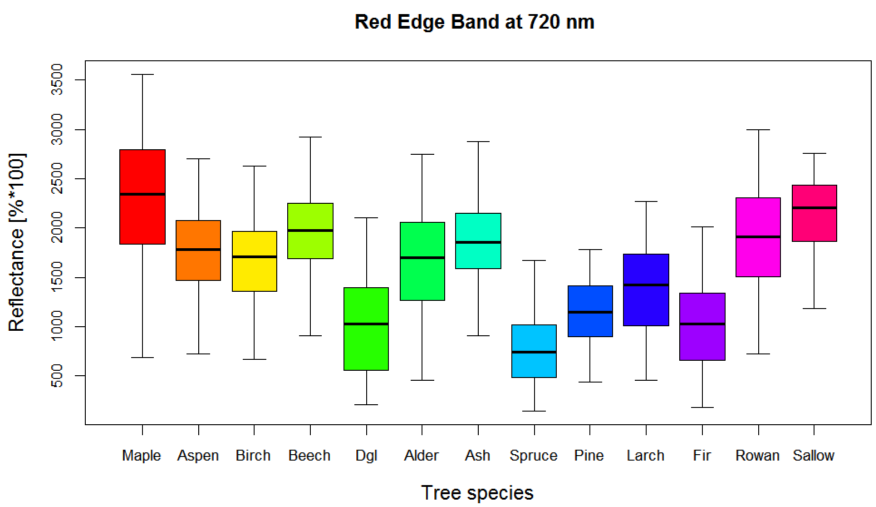
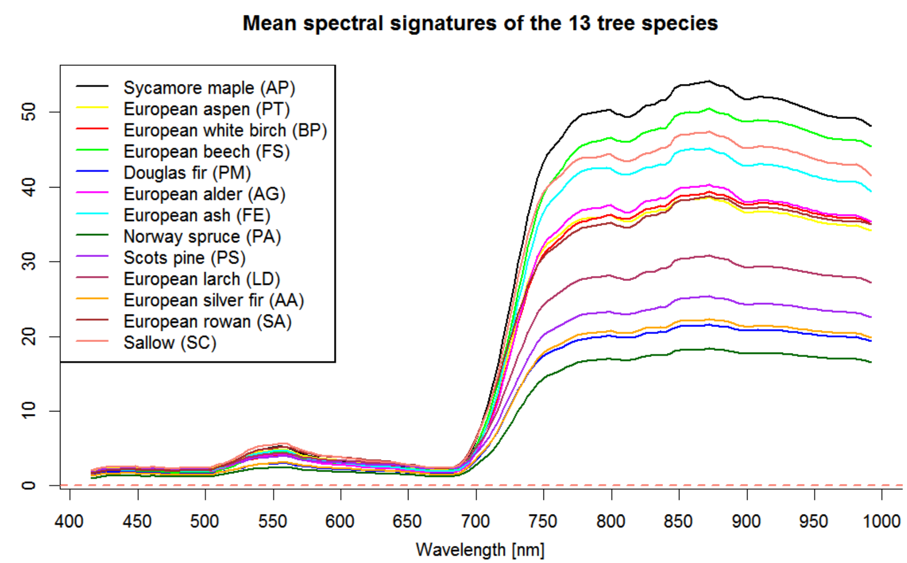
Challenge

Capture the complex inter- and intra-species spectral variability and the problem of spectral similarity.





→Additional data needed (LiDAR, Vegetation indices etc.)

Optimal ground sampling density and spatial unit

Ground sampling density and spatial unit

- What is the spatial unit on which species information should be obtained ?

- What is the optimal ground sampling density (pixel size) of a given sensor to derive tree species information

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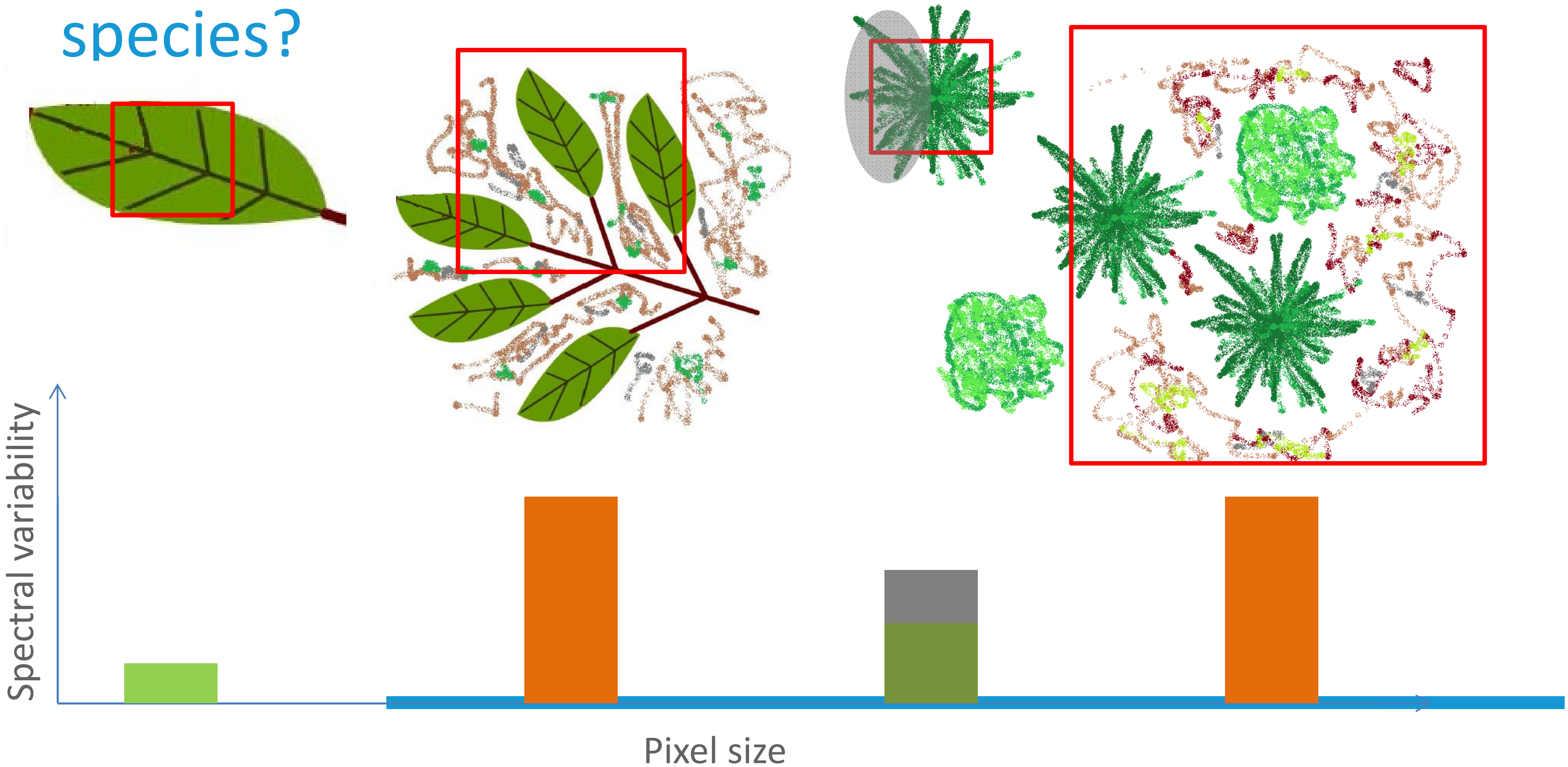
Spatial resolution and scale

- Complex interplay of radiation with crown tissues (foliage, stems, branches, fruits, lianas and flowers)
- background signal (stemming from soil, herbaceous vegetation)
- structural arrangement of foliage (number of layers, clumping and leaf angles) and shadow fractions
- View-illumination geometry

Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

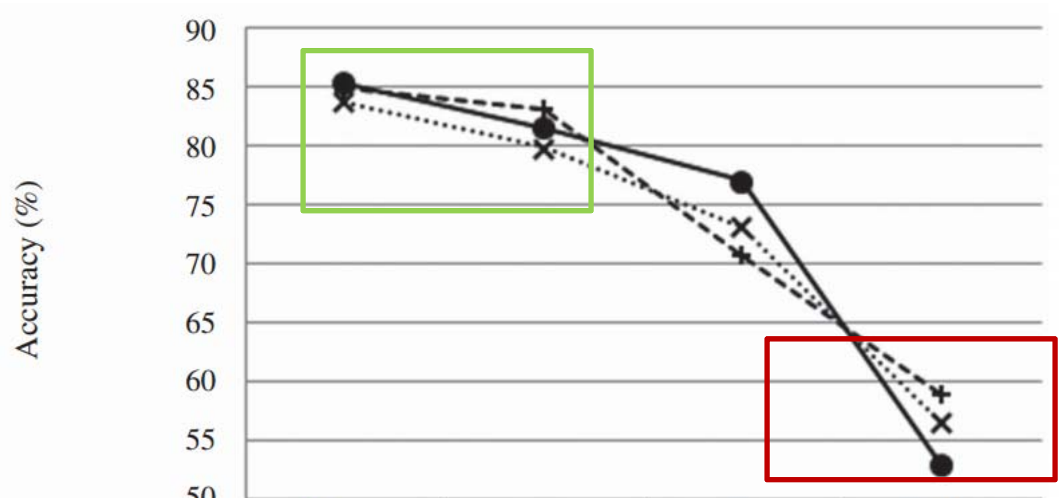


Fassnacht (2015)

Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

Experiences from case studies (II)



	0.3 m	0.6 m	1.2 m	2.4 m
160 bands	85.3	81.5	77.0	52.9
79 bands	83.8	79.8	73.1	56.5
39 bands	84.8	83.1	70.7	59.0

Pena, M.A., Cruz, P. & Roig, M. (2014). The effect of spectral and spatial degradation of hyperspectral imagery for the Sclerophyll tree species classification. Int. J. of Rem. Sens., 34(20), 7113-7130.

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Spatial resolution and scale

What is the optimal pixel size for classifying tree species?

Case studies suggest:

Either possibly small pixels (< 0.5 m)

Or: pixels close to the size of an individual crown

BUT: So far the spatial unit was a pixel!

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Spatial resolution and scale

What is the optimal spatial unit to obtain species information?

Three obvious approaches:

(I) Pixel
(II) Single-tree objects
(III) Stands or other operational unit

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Spatial resolution and scale

What is the optimal spatial unit to obtain species information?

Advantages of object-based approaches (single tree and stand-level) in case accurate objects can be obtained:

- Meaningful units (practitioners work with it)
- Combination of LiDAR and Hyperspectral becomes more powerful:
  - Normalization of spectra (sunlit parts of the crowns)
  - Majority voting approaches
  - Single-tree based geometric information (crown-base height, canopy transects, crown volume, …)
  - Density information from LiDAR + spectral information from satellites

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Spatial resolution and scale

What is the optimal spatial unit to obtain species information?

Challenges of object-based approaches (single tree and stand-level):

- The quality of the results largely depends on the delineation success

- Classifications on stand-level-objects have to consider that differing forest densities may lead to very distinct reflectance signals for the identical species composition

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Spatial resolution and scale

- An argument for small pixel sizes is that the increased spectral variability can be methodically addressed by applying object-based approaches.
- The distribution of spectral signatures of the pixels within a crown object could vary amongst species and therefore contain relevant information.
- Optimal spatial resolution will also depend on the applied methods and the forest types under investigation.

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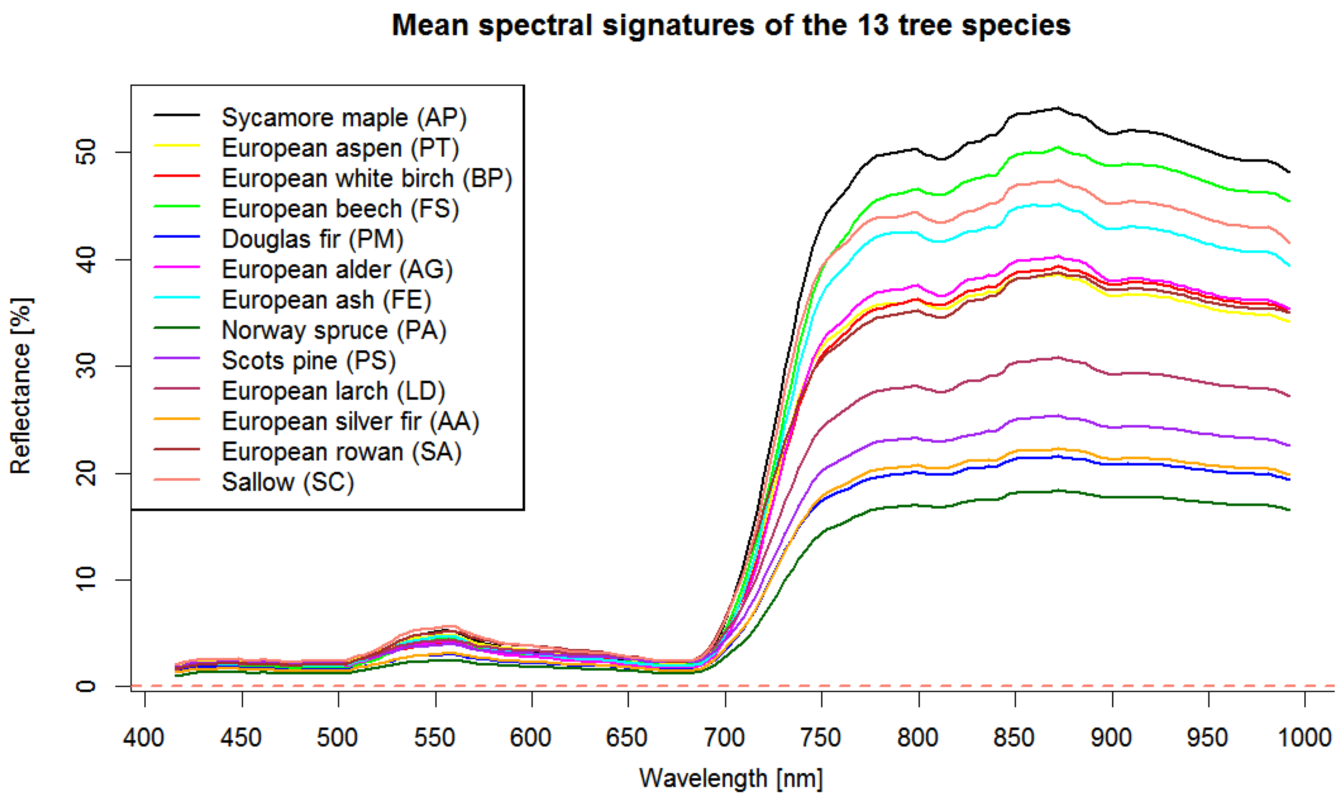
Spectral resolution and range

Spectral resolution and range

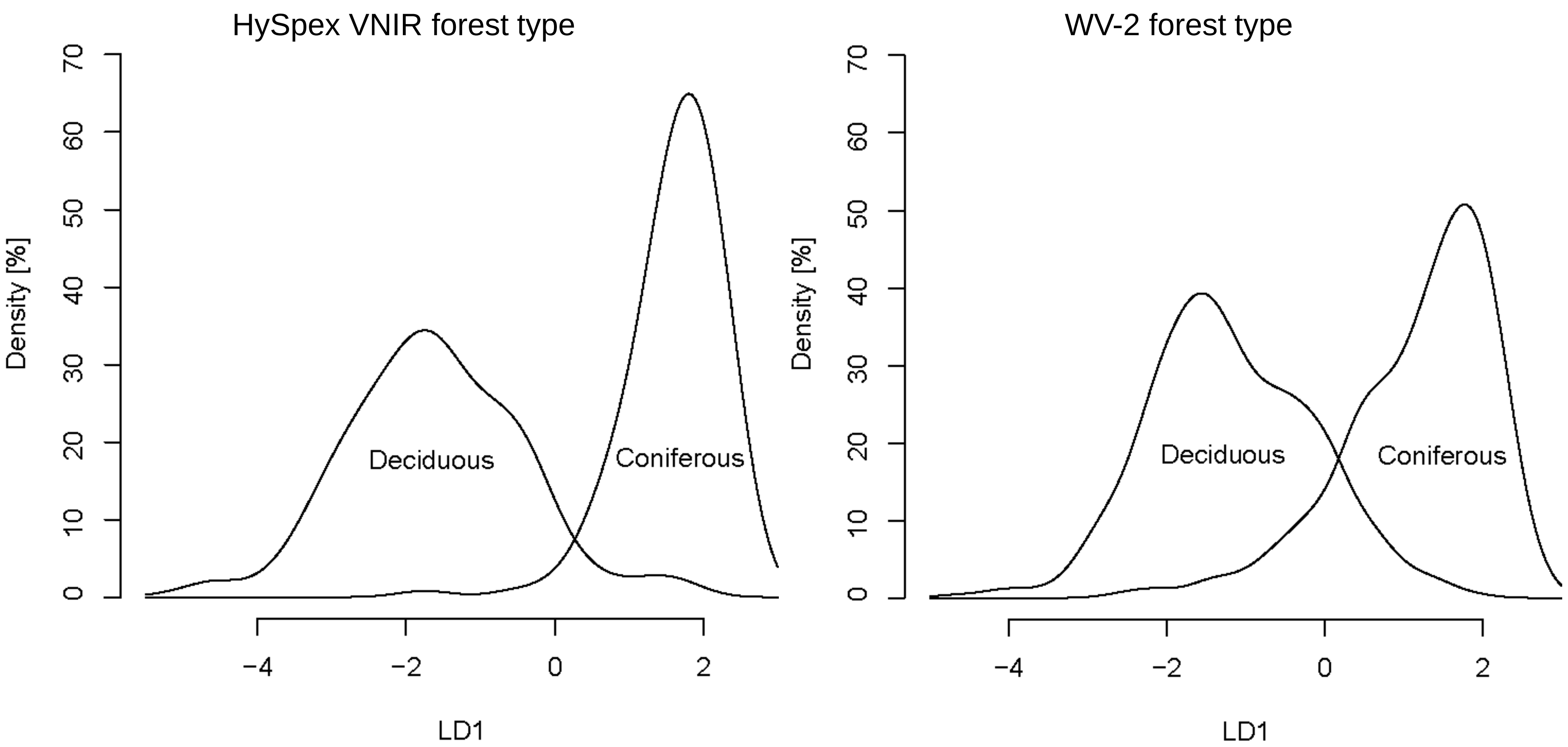
- Do we need to cover the full VIS-SWIR region?
- How narrow should the bands be?
- How to deal with spectral resolution in an operational approach?

Spectral resolution and range

Capture the complex inter- and intra-species spectral variability and the problem of spectral similarity.



Spectral resolution and range



A. Reichmuth (2013)

Spectral resolution and range

Species–related traits mesured by RS

- Important wavelength regions
- Texture information
- Phenology
- Ecotypes, site condition and leaf age

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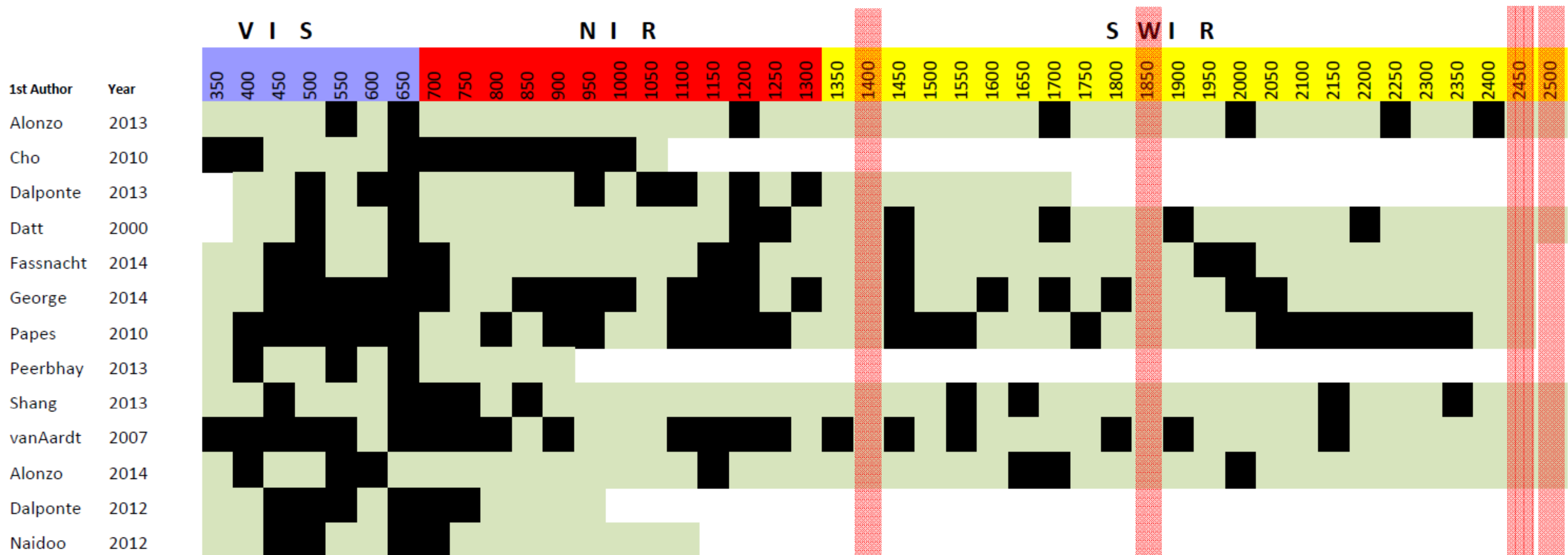
Species related traits

Important wavelength regions



	350	400	450	500	550	600	650	700	750	800	850	900	950	1000	1050	1100	1150	1200	1250	1300	1350	1400
covered	11	13	13	13	13	13	13	13	13	13	13	13	12	11	11	10	9	9	9	9	9	9
selected	2	5	7	7	7	4	12	7	4	3	3	4	4	2	1	4	5	7	3	2	1	0
perc. sel.	18	38	54	54	54	31	92	54	31	23	23	31	33	18	9.1	40	56	78	33	22	11	0

	1450	1500	1550	1600	1650	1700	1750	1800	1850	1900	1950	2000	2050	2100	2150	2200	2250	2300	2350	2400	2450	2500
covered	9	9	9	9	9	9	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	5
selected	5	1	3	1	2	4	1	2	0	2	1	4	2	1	3	2	2	1	2	1	0	0
perc. sel.	56	11	33	11	22	44	13	25	0	25	13	50	25	13	38	25	25	13	25	13	0	0

selected features

spectral range of sensor in study

selected in more than 50% of the considered studies

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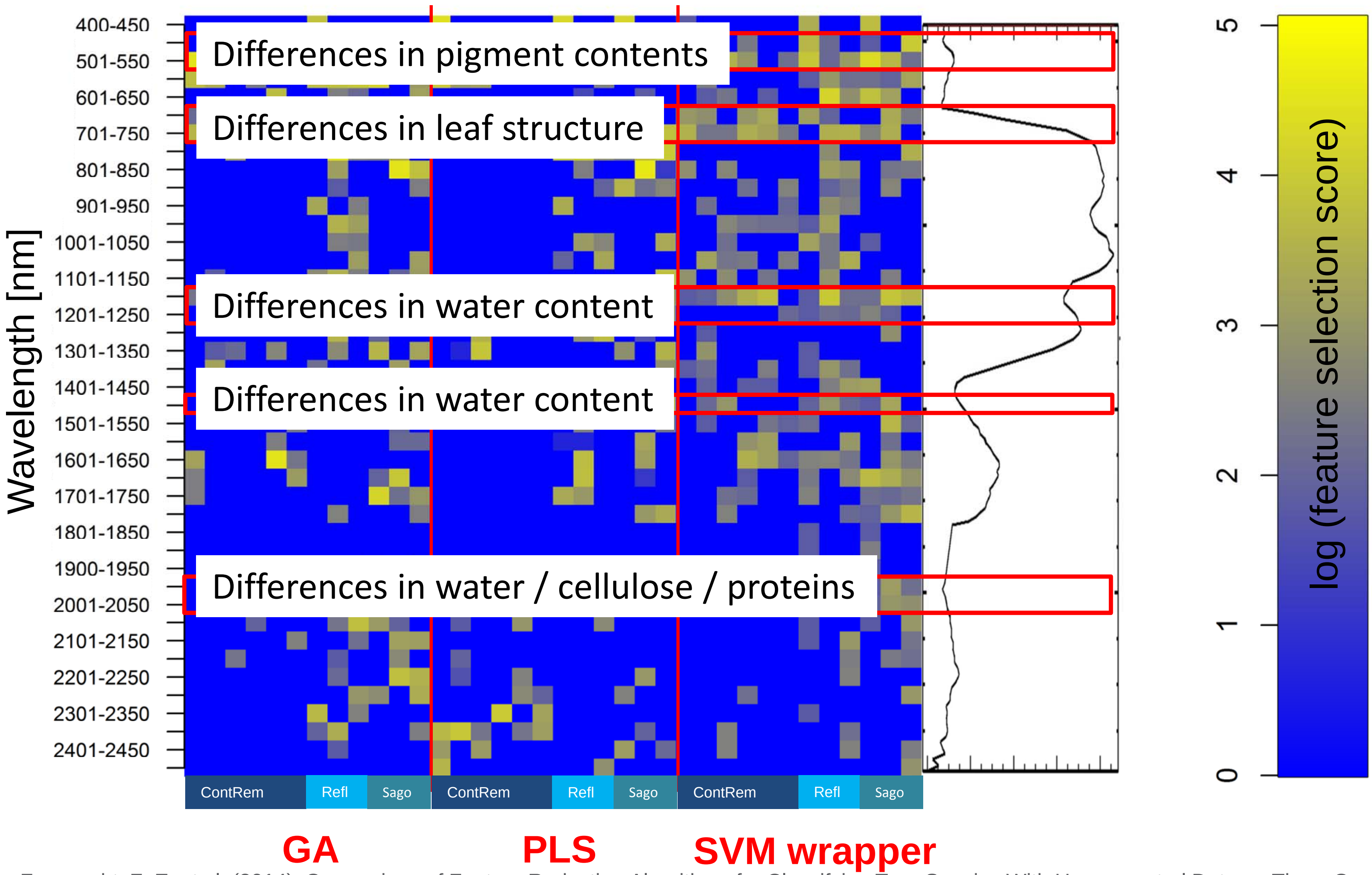
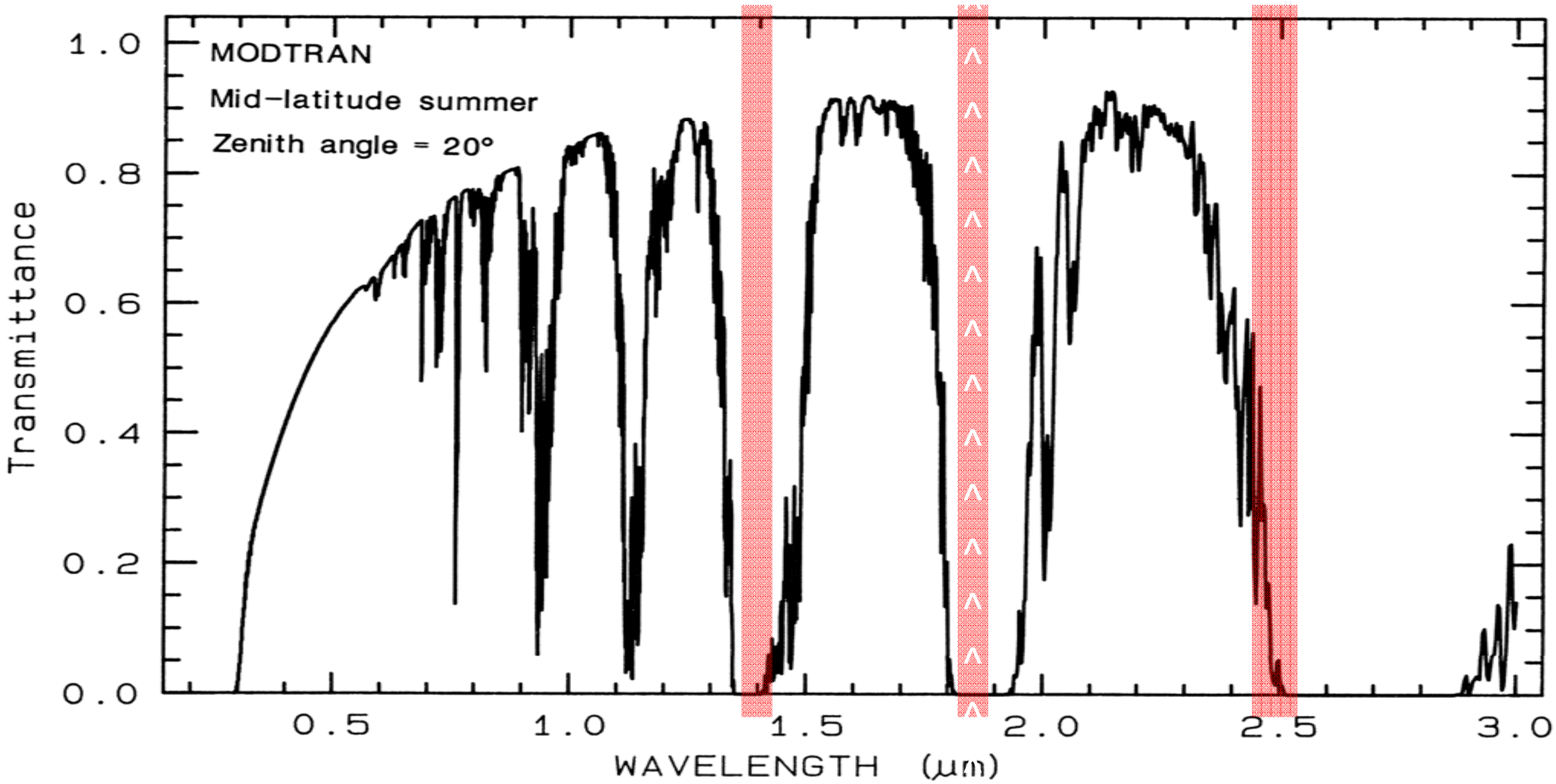
Importance of spectral regions



Fassnacht, F. E. et al. (2014): Comparison of Feature Reduction Algorithms for Classifying Tree Species With Hyperspectral Data on Three Central European Test Sites. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (J-STARS) 7(6), pp. 2547–2561.

Species related traits



http://speclab.cr.usgs.gov/PAPERS.refl-mrs/giff/300dpi/fig3a3.gif

Species related traits

Crown Texture

- Mainly related to crown-internal shadows, foliage properties (size, density, reflectivity) and branching
- On coarser scales, crown size, crown closure, crown shape, stand density and forest type (broadleaved, coniferous) are the main driver for texture in passive optical imagery.
- Owing to the multiscale perspective of texture, the optimum window size varies for example with the crown diameter of a specific tree.

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Species related traits

Phenology

- Coloring of leaves due to senescence (faster decomposition of chlorophyll pigments in comparison to Anthocyanins and Carotenoids)
- Green colours of fresh leaves and needles (flowering events)
- Species specific knowledge is preferable over forest phenology
- Image acquisition aligned with phenological cycle is desirable

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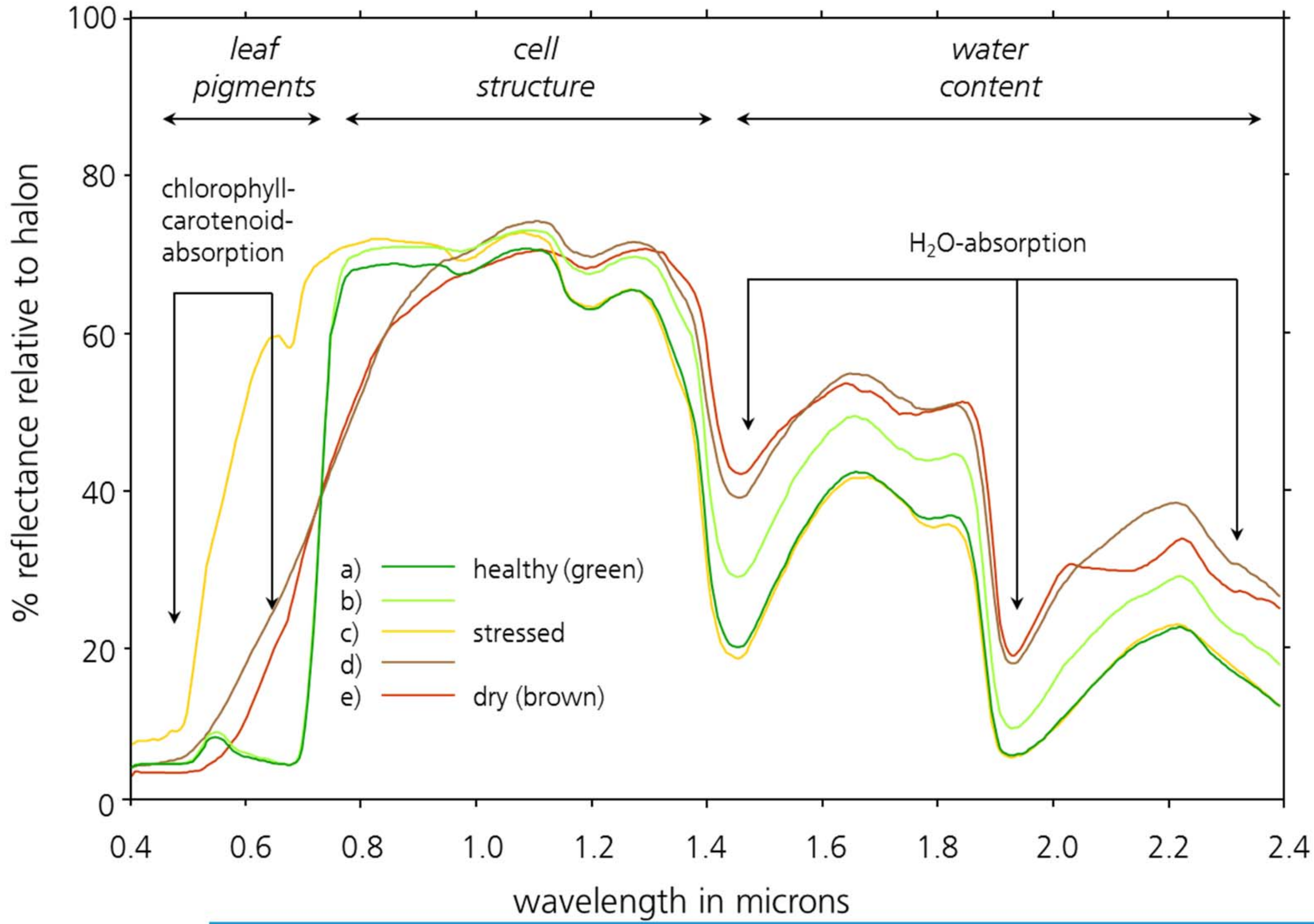
Spectral resolution and range



Species related traits

Ecotypes, site condition, leaf age

- Reflectance differences between the same species at different locations
- Mostly related to variable site conditons (at larger geographic extents)

Species related traits

LiDAR

- Mainly structure information
- Architecture of crowns, branching, and foliage
- The intensity of backscattered signal is connected to foliage type, leaf type , leaf orientation, leaf dumping and foliage density

Mid-infrared and thermal-infrared sensors

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Spectral resolution and range

- Do we need to cover the full VIS-SWIR region?
- Based on the studies so far: Yes!
- But: some regions are more important than others

→ optimize processing speed?

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Spectral resolution and range

- How narrow should the bands be?
- Question is connected to processing speed (number of predictors)
- Radiometric noise vs. ability to capture subtle absorption features
- Hardly any systematic investigation available so far

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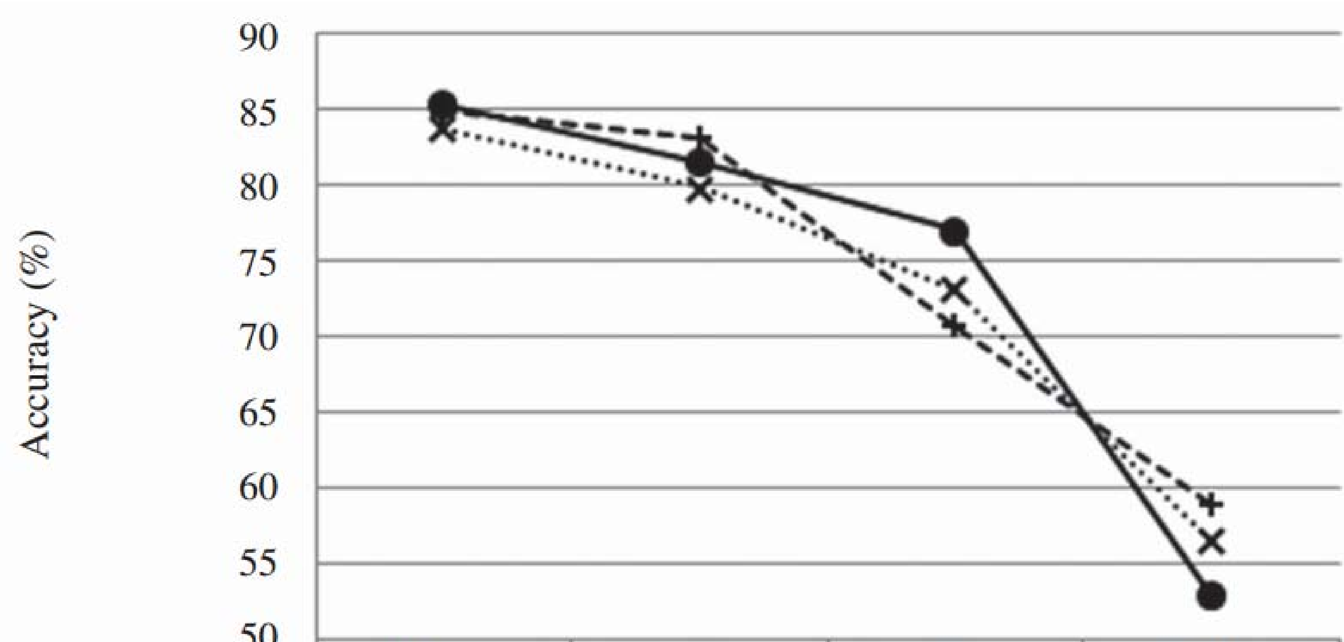

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160 bands	85.3	81.5	77.0	52.9
79 bands	83.8	79.8	73.1	56.5
39 bands	84.8	83.1	70.7	59.0

Results for SAM classifier applied to noise-reduced image (MNF)

Pena, M.A., Cruz, P. & Roig, M. (2014). The effect of spectral and spatial degradation of hyperspectral imagery for the Sclerophyll tree species classification. Int. J. of Rem. Sens., 34(20), 7113-7130.

Spectral resolution and range

- How narrow should the bands be?
- “Gut feeling / hypothesis”:
- A sensor with 100-150 narrow bands (VIS-SWIR) should do the job
- Having very narrow 400 bands won’t add a lot of useful information in a classification problem (co-linearity)

Methods for tree species classificaton

Reference data

- Considered classes have to match the research question
- The data should be represenative for the site of investigation
- The spatial scale should match the problem under investigation
- The data should acknowledge the underlying assumption of applied methodology (e.g. minimum number of samples per class etc.)
- Observation errors should be known and their impact on the results should be discussed
- Samples should be spatially independent

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Methods for tree species classificaton

- Calibration and validation
- Simple data splitting (70% of training, 30% of validation)
- X-fold cross validation (samples are randomly split into x parts (folds) of equal sample size)
- Bootstrap – resampling (n -reference samples get sampled n times with replacement (out of bag validation of random forest (RF))
- Recommendeation iterative data splitting approach and an additional completely independent test set as a gold standard for tree species classification studies.

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Methods for tree species classificaton

- Feature reduction
  - Feature extraction methods (MNF, PCA, SVM) selects a subset of the original predictor variables)
  - Feature selection methods (Stepwise procedures, RF, GA) calculates new predictor variables that typically summarize the content of several original predictors)

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Methods for tree species classificaton

- Classification algorithm
- Non-parametric machine learning methods (RF, SVM), using mixed sets of input variables (spectral, texture, geometric, indices)

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Methods for tree species classificaton

Classification approach	Advantage	Disadvantage
Discriminant Analysis (linear, quadratical, canonical, stepwise, regularized, penalized)	LDA does not require the tuning of parameters Accepts multiple input variables. Easier interpretation of Between-class differences	Assumes Gaussian distribution of training data Classical discriminant analyses are less sensitive to ill-posed problems and outliers. Noisy results in complex landscapes. Limited ability to deal with multi-colinearity
Maximum Likelihood	Consistent approach for a variety of estimation Problems Approx. unbiased in presence of larger sample sizes. Many software implementations.	Assumes Gaussian distribution of training data Biased for small samples . Sensitive to the number of input variables
Random Forest (RF)	No distributional assumption required Less sensitive to the number of input Variables Less sensitive to overfitting	Might overfit in presence of noisy data. Might be biased in case response classes have different number of levels
SVM	No distributional assumption required. Suitable when incorporating non-remote sensing variables into classification robust to noise and high-dimensional data fast predictions (sparse model due to support vectors).Comparably few training data needed. Possibility to easily access probability values instead of only discrete classes	Optimal design of a multi-class SVM is demanding Comparatively high computational cost (algorithmic complexity) for training Selection of kernel function parameters
Neural Networks	Able to extract patterns and identify trends from pool of data Implemented by many software packages Suitable to deal with classification problems which are hardly mathematically definable	Difficult to train, since the results are ultimately dependent on the initial parameters Black box-like setup

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Methods for tree species classificaton

- Atmospheric correction
- Anisotropy effects: brightness of an observed object depends on the view illumination geometry (BRDF)
- Data fusion

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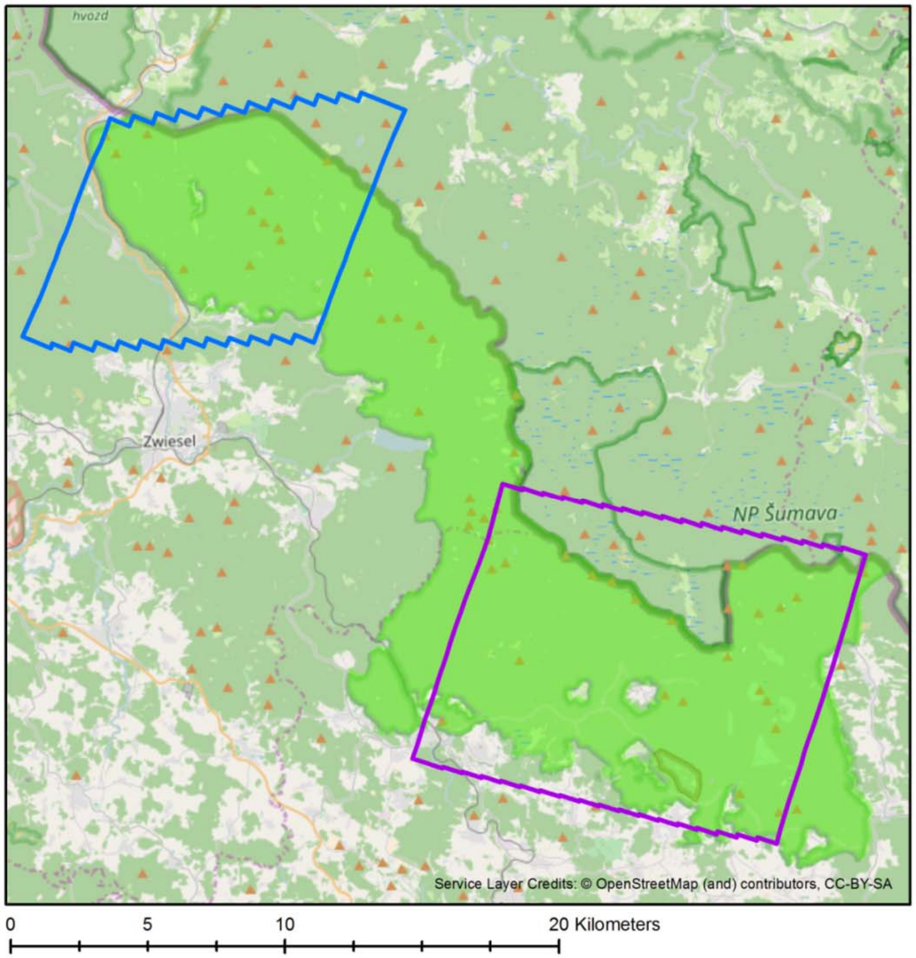
Case Study
Bavarian Forest National Park

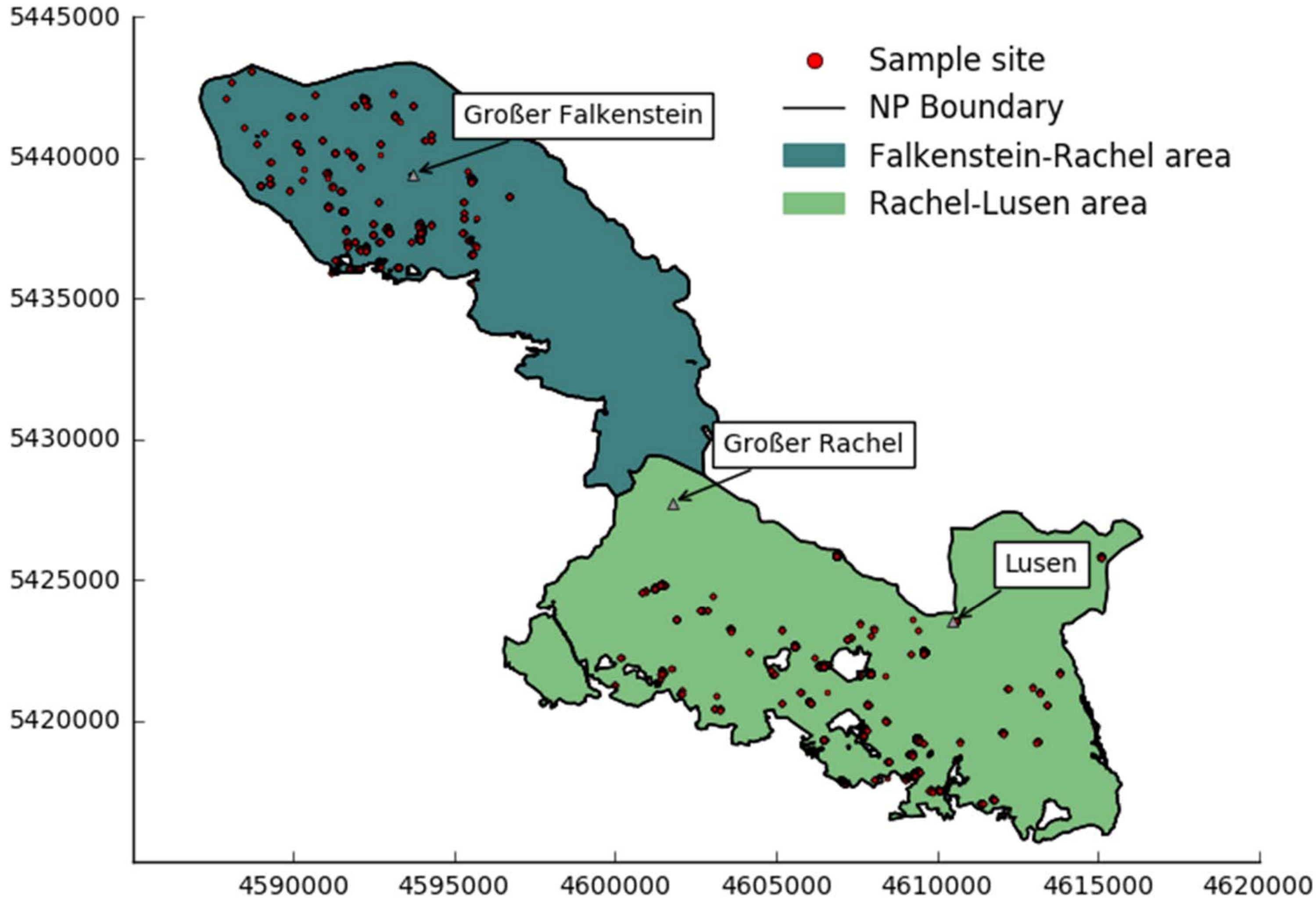
- First National Park in Germany
  - Founded: 1970
  - Enlarged: 1997
- Currently: 24.369 ha
- 22 tree species

Bavarian Forest National Park

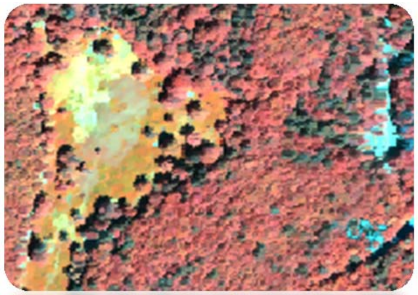


Data acquisition 22. & 27.7.2013
1.6m / 3.2m pixel resolution

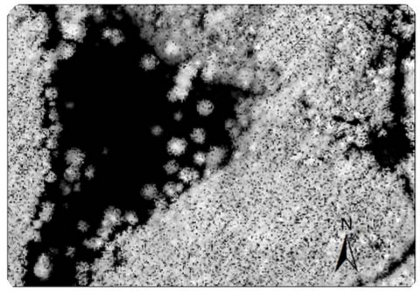
Bavarian Forest National Park



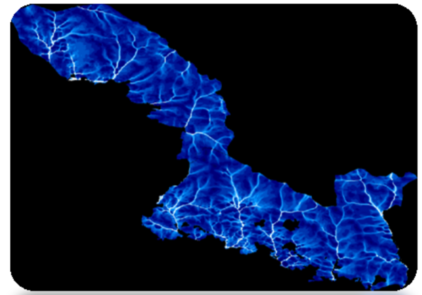
Species Related Feature Extraction



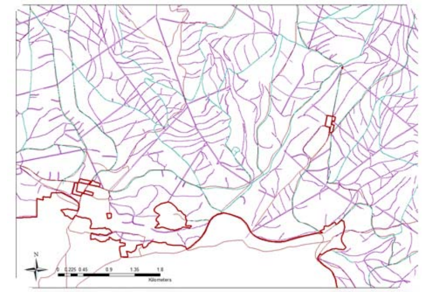
- Spectral information
- Vegetation indices
- EBVs



- Tree height
- Ilumination condition
- Site characteristics
- Elevation
- Deciduous
- Coniferous



- Soil moisture

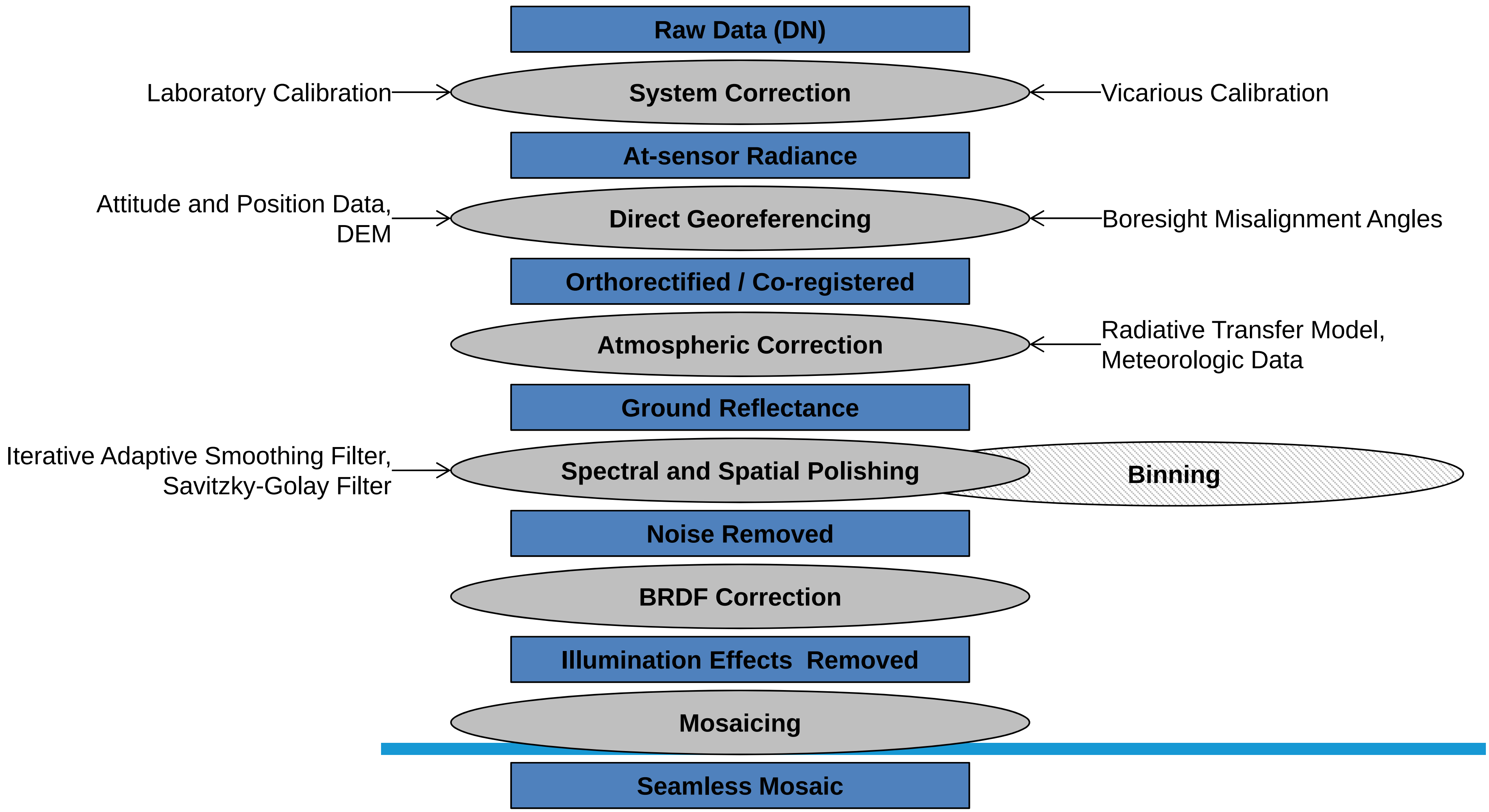


- Habitat type

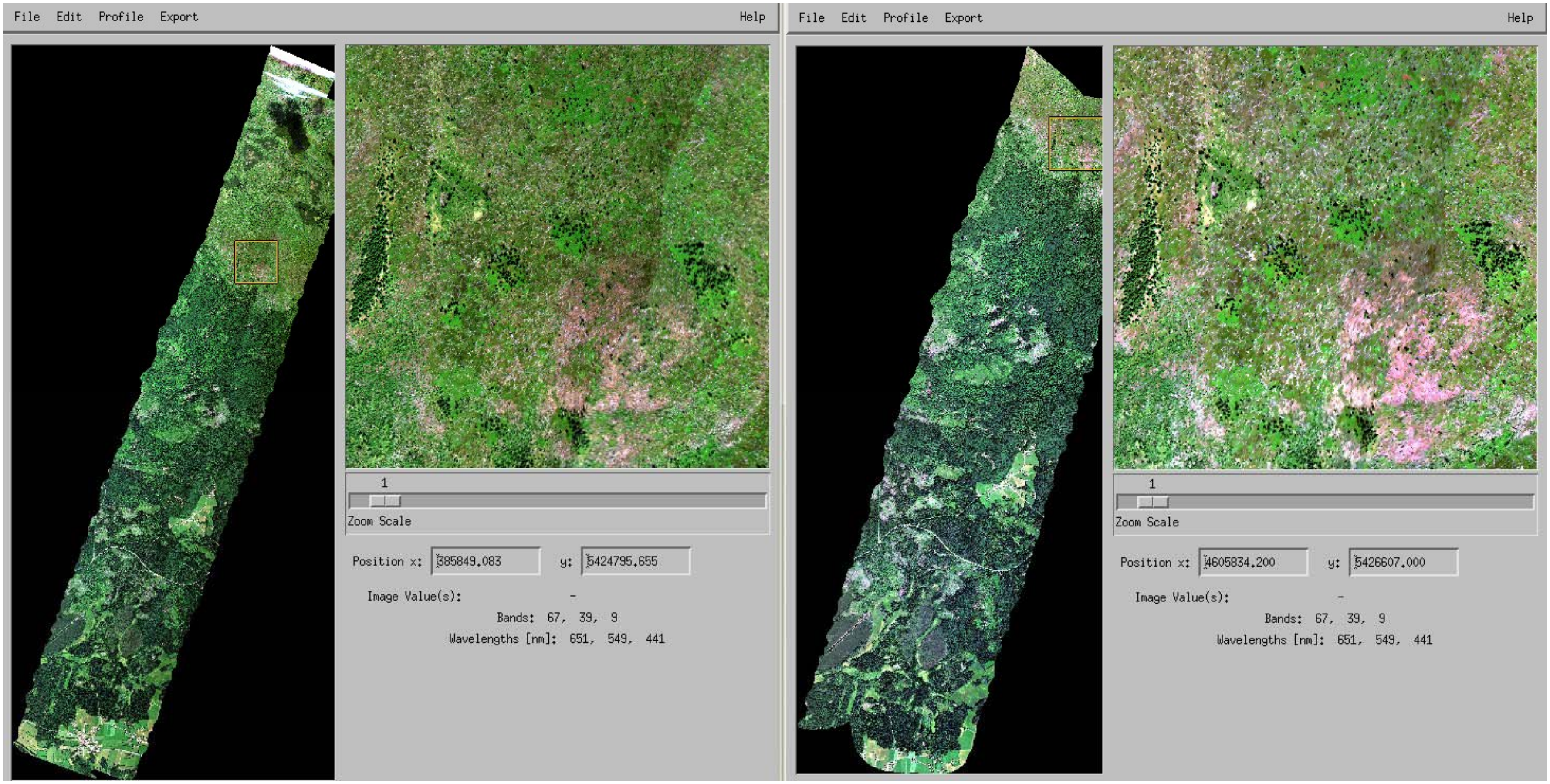
Classification of tree species on the basis of different features derived from remote sensing data and available site specific information

Which spectral/spatial features and data combinations generate the best results within a classification modelling approach?

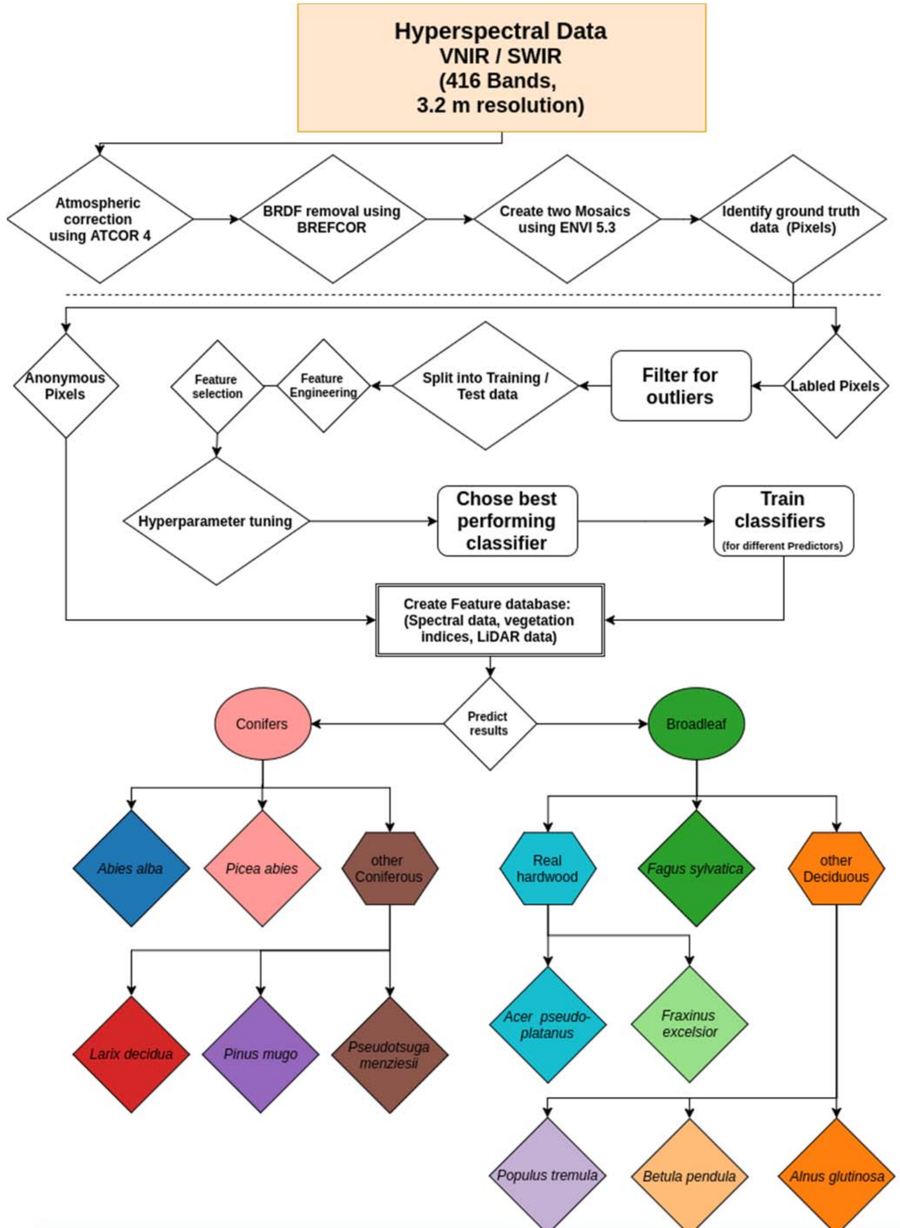
Preprocessing Steps of Hyperspectral Data



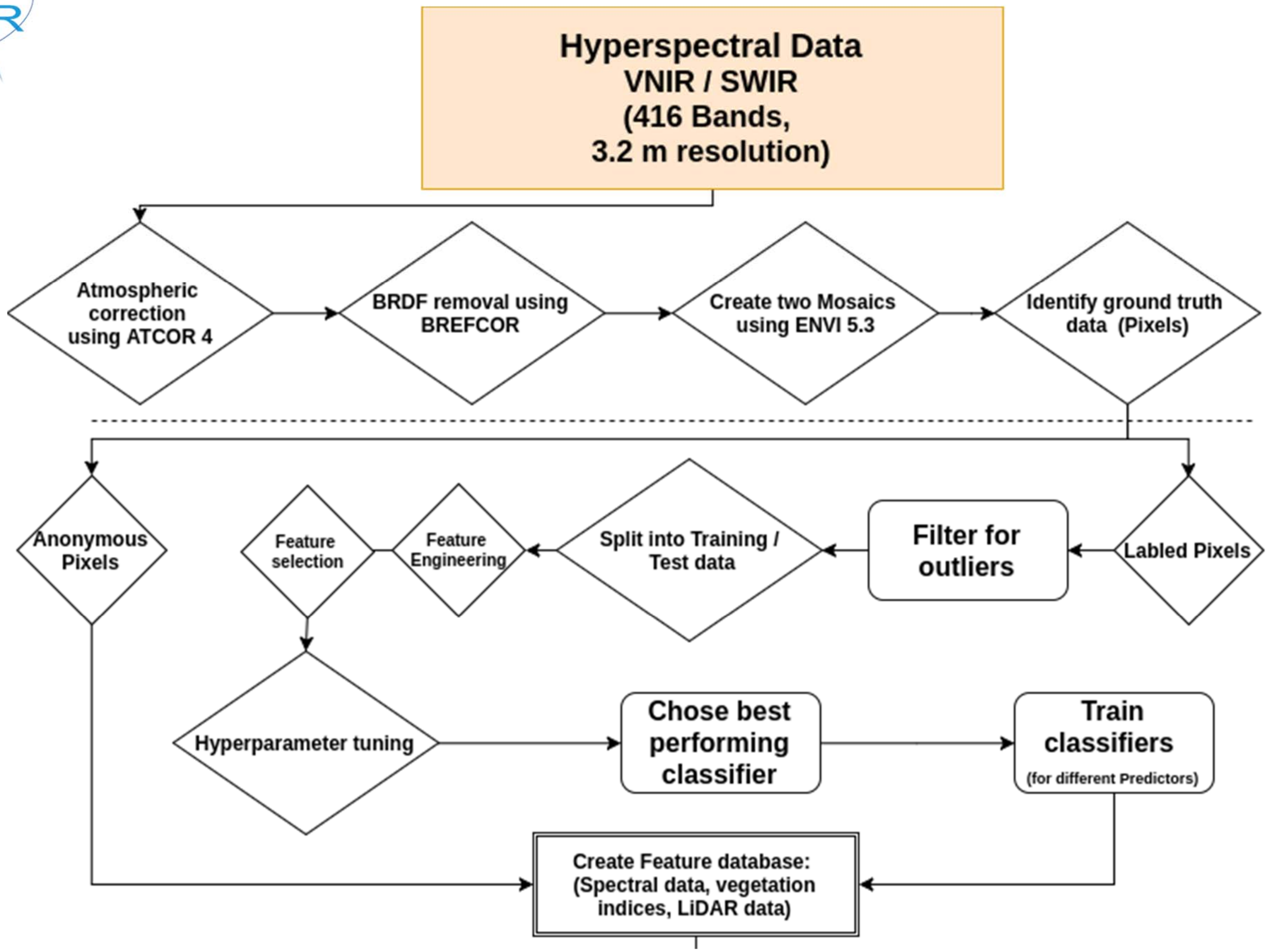
BRDF Correction



BRDF effects correction method (BREFCOR – ATCOR4) for an unsupervised, model based BRDF correction (surface-cover-dependent) of airborne wide FOV scanner data



Hyperspectral Data
VNIR / SWIR
(416 Bands,
3.2 m resolution)
Atmospheric correction using ATCOR 4
BRDF removal using BREFCOR
Create two Mosaics using ENVI 5.3
Identify ground truth data (Pixels)
Anonymous Pixels
Feature selection
Feature Engineering
Split into Training / Test data
Filter for outliers
Labled Pixels
Hyperparameter tuning
Chose best performing classifier
Train classifiers
(for different Predictors)
Create Feature database:
(Spectral data, vegetation indices, LiDAR data)
Conifers
Predict results
Broadleaf
Abies alba
Picea abies
other Coniferous
Real hardwood
Fagus sylvatica
other Deciduous
Larix decidua
Pinus mugo
Pseudotsuga menziesii
Acer pseudo-platanus
Fraxinus excelsior
Populus tremula
Betula pendula
Alnus glutinosa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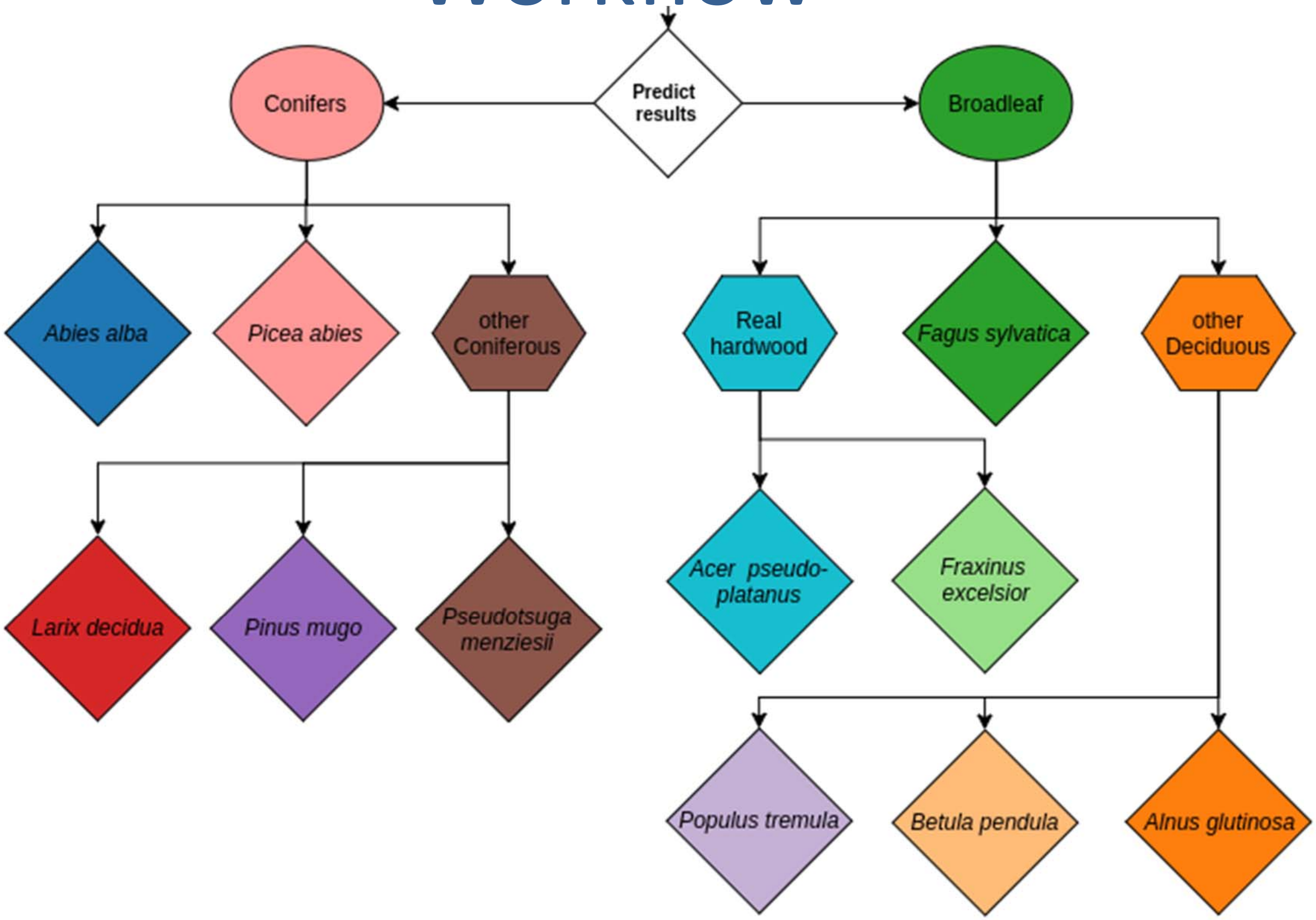
Workflow


Predict results
Conifers
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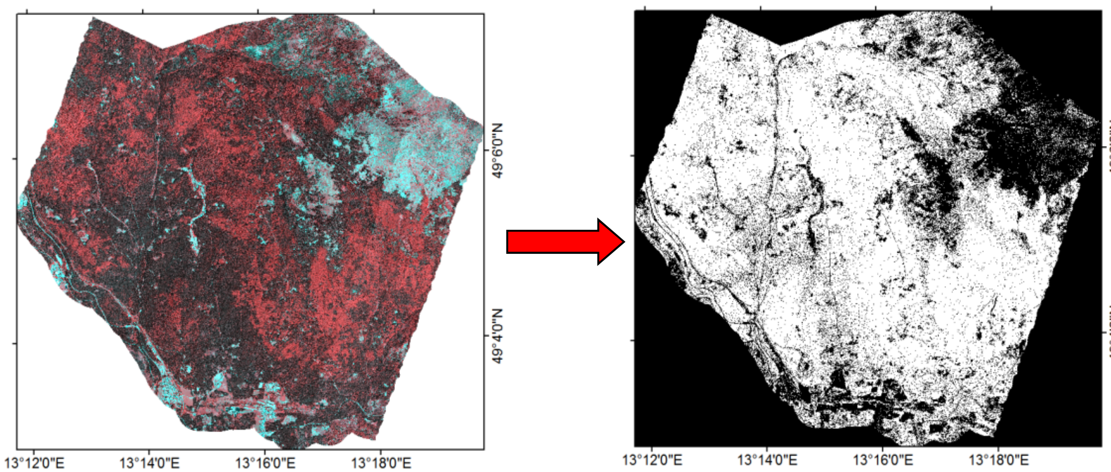
other Deciduous
Larix decidua
Pinus mugo
Pseudotsuga menziesii
Acer pseudo-platanus
Fraxinus excelsior
Populus tremula
Betula pendula
Alnus glutinosa

Forest / Tree Mask

✓Ensures, that only trees are classified

✓Prevents misclassification between trees and other vegetation

1. Discriminate between vegetation (NDVI ≥ 0.4) and non-vegetation (NDVI < 0.4)
2. Eliminate Forest gaps and low canopy heights
   (LiDAR derived tree heights < 1.5m)



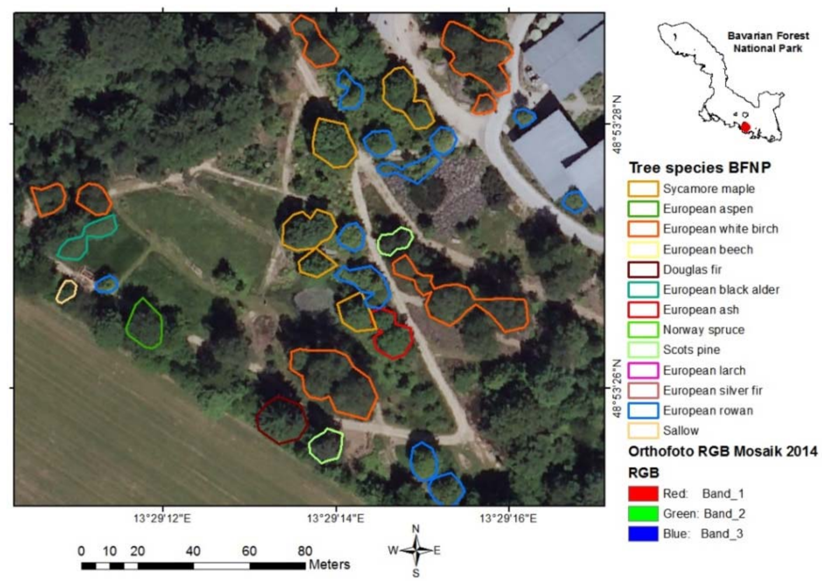
In-situ Data

Set-up of training and validation data→ reference data set

Depending on geometric resolution of remote sensing data:
Single trees → crown
Plots of trees → cluster of crowns / stands

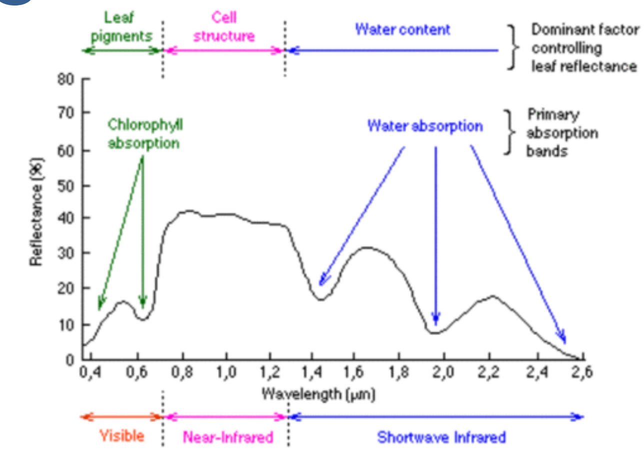
Minimum number of samples
> 10·n pixels (desirably 100·n pixels)
where n = number of variables used
to extract classes

Imbalanced training data set
→ down-sampling approach



Reference data set should cover all possible feature specific variations of the occurring tree species

Vegetation Indices



Photochemical Reflectance Index $PRI = \frac{\lambda_{531nm} - \lambda_{570nm}}{\lambda_{531nm} + \lambda_{570nm}}$

→ e.g. vegetation productivity

Red Edge NDVI $RENDVI = \frac{\lambda_{750nm} - \lambda_{705nm}}{\lambda_{750nm} + \lambda_{705nm}}$

→ e.g. general vegetation health

Red Edge Inflection Point $REIP = 700 + 40 \cdot \left[\frac{\left(\frac{\lambda_{670nm} + \lambda_{780nm}}{2} - \lambda_{700nm} \right)}{(\lambda_{740nm} - \lambda_{700nm})} \right]$

→ e.g. chlorophyll content

Simple Ratio $SR = \frac{NIR}{RED}$

→ e.g. estimation of over-story LAI

Normalized Difference Infrared Index $NDII = \frac{\lambda_{819nm} - \lambda_{1649nm}}{\lambda_{819nm} + \lambda_{1649nm}}$

→ e.g. plant water content

Normalized Difference Lignin Index $NDLI = \frac{\left(\log \frac{1}{\lambda_{1754nm}}\right) - \left(\log \frac{1}{\lambda_{1680nm}}\right)}{\left(\log \frac{1}{\lambda_{1754nm}}\right) + \left(\log \frac{1}{\lambda_{1680nm}}\right)}$

→ Lignin content

Structural and Topographic Features

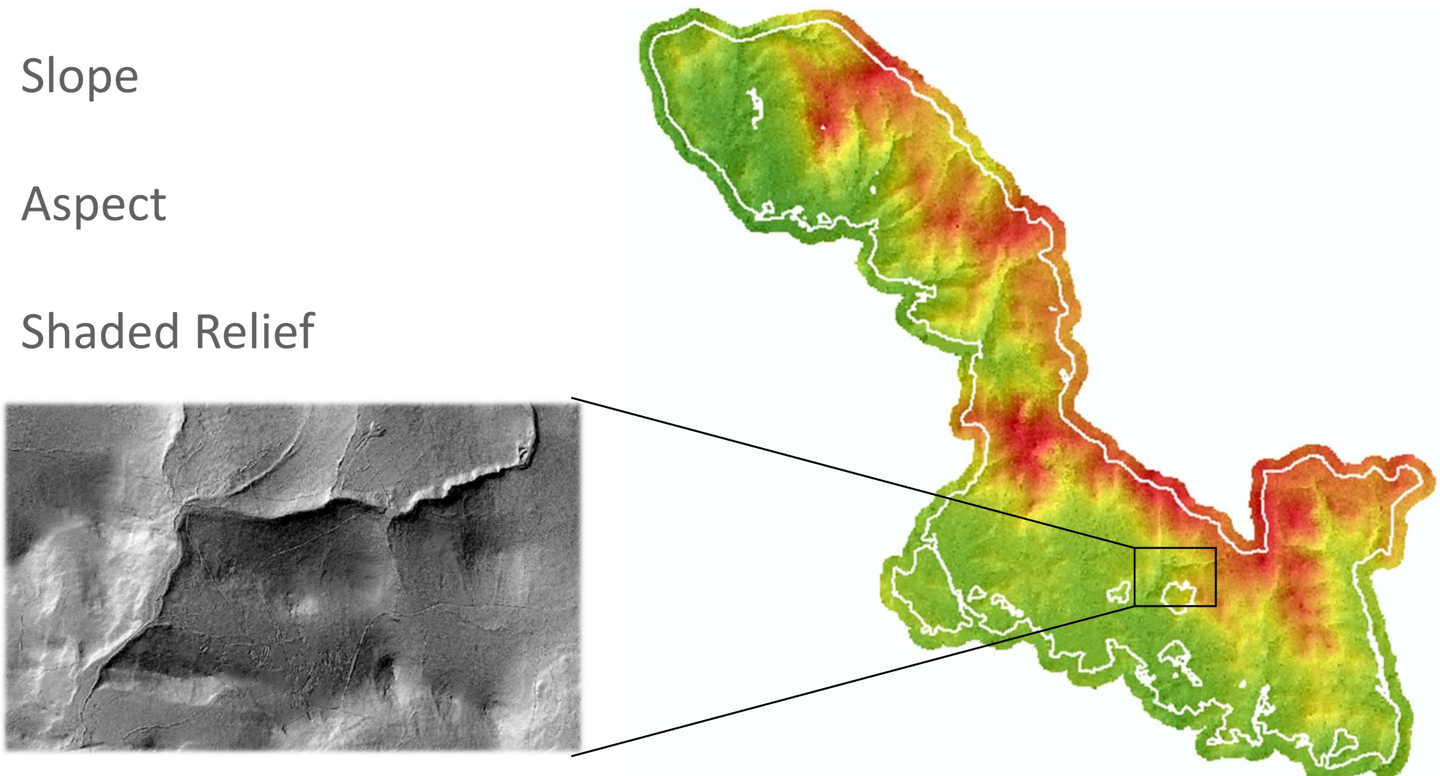
→ Tree height (DSM – DEM)

→ Terrain height (DEM)

→ Slope

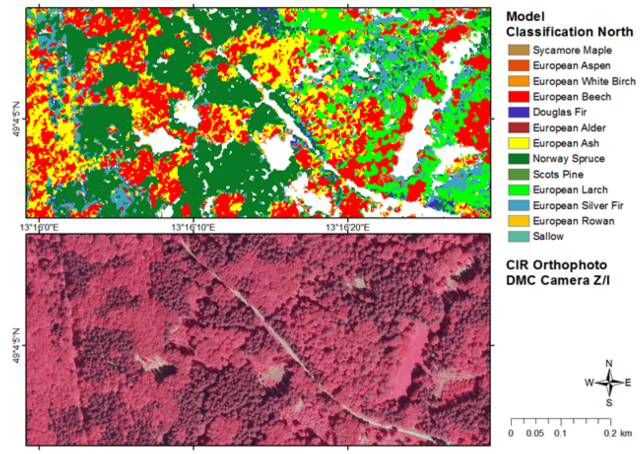
→ Aspect

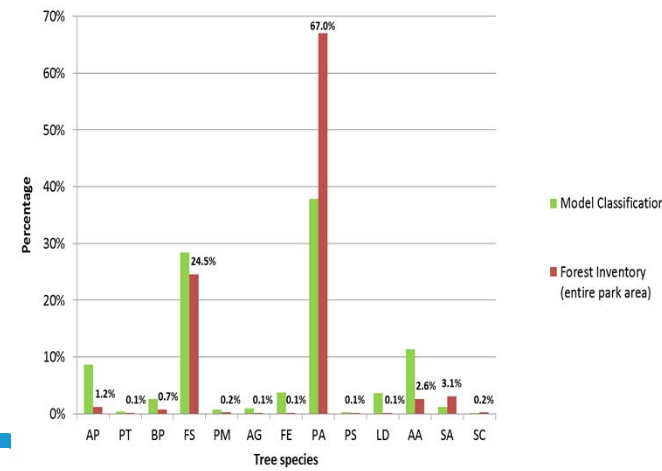
→ Shaded Relief



Validation Approach

- Evaluation of classification accuracy
- Test data set
  (statistical evaluation – confusion matrix)
- Visual interpretation
- Forest inventory
- Field survey





Accuracy assessment

Evaluation based on Cohen‘s kappa and F-Scores

$$\text{Kappa: } \kappa = (p_o - p_e)/(1 - p_e)$$

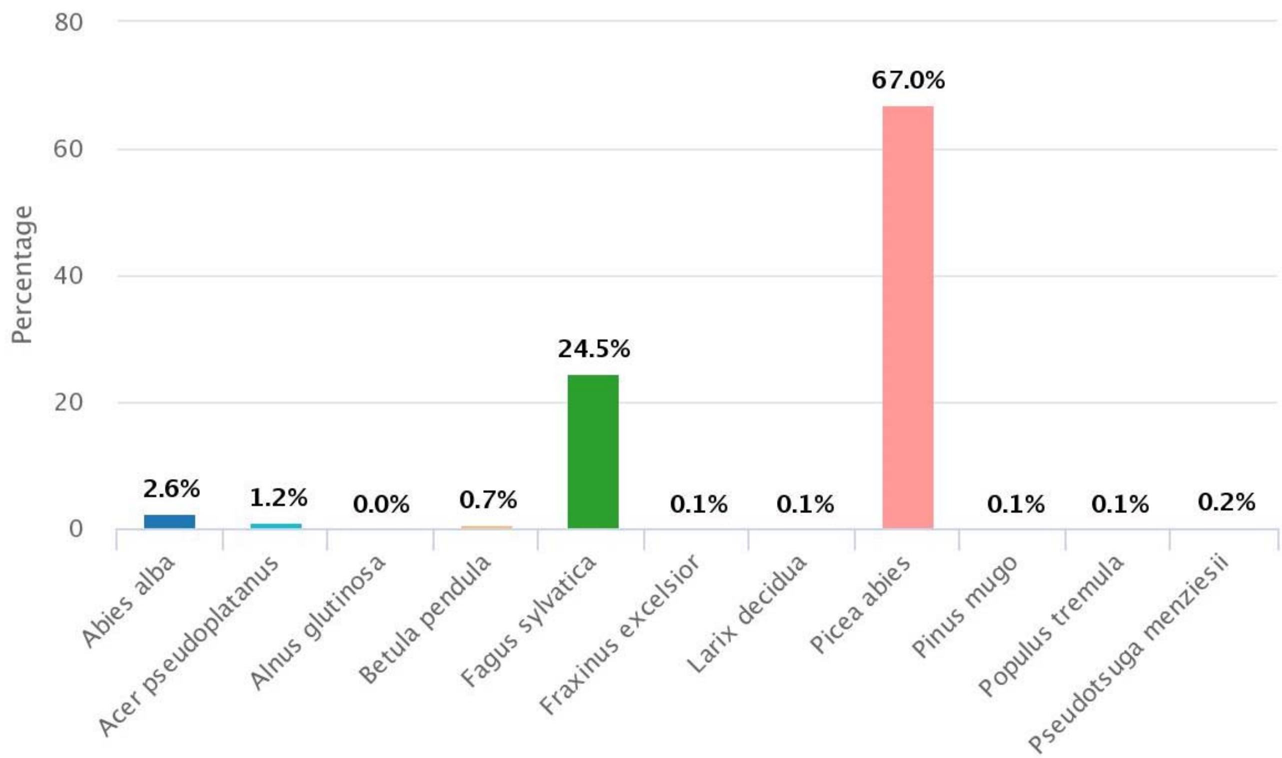
p istheobservedagreementratio,and
p istheexpectedagreement.

$$\text{F1score: } F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

$$\text{precision} = \frac{tp}{tp + fp} \qquad \text{recall} = \frac{tp}{tp + fn}$$

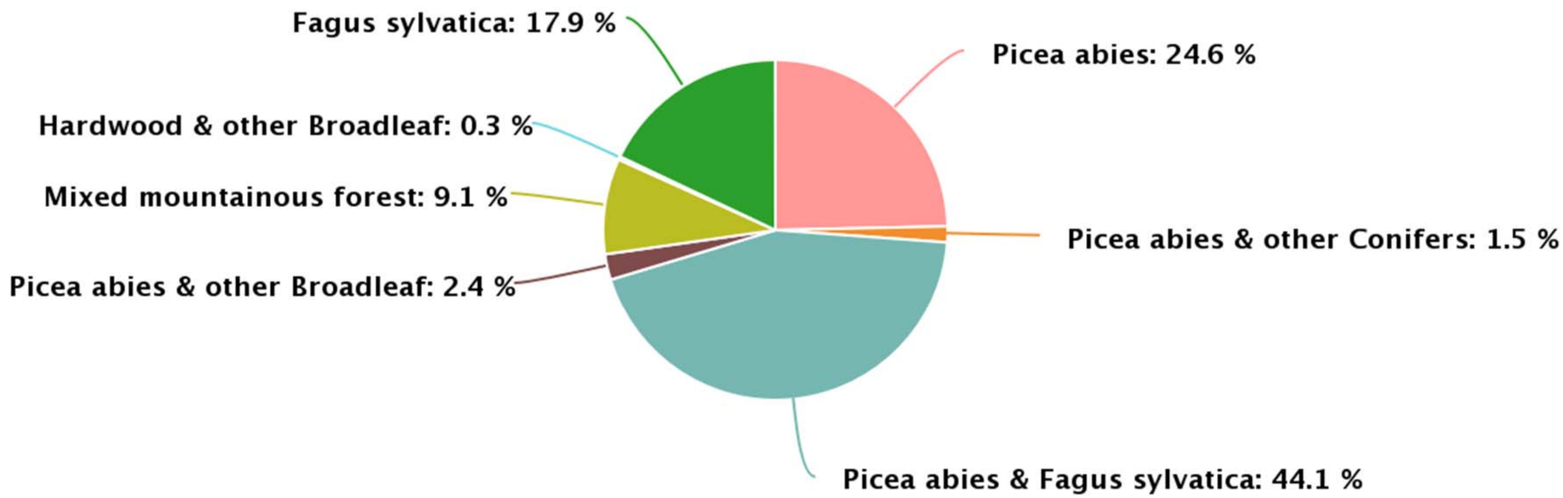
Training Data

Forest Inventory 2002/2003



Training Data

Species composition northern part



Training Data

Species	English	Abbrevation	Pixels	Color
Abies alba	European silver fir	**AA**	543	
Acer pseudoplatanus	Sycamore maple	**AP**	371	
Alnus glutinosa	European alder	**AG**	204	
Betula pendula	Silver birch	**BP**	329	
Fagus sylvatica	European beech	**FS**	1408	
Fraxinus excelsior	European ash	**FE**	386	
Larix decidua	European larch	**LD**	346	
Picea abies	Norway spruce	**PA**	725	
Pinus mugo	Mountain pine	**PMu**	237	
Populus tremula	European aspen	**PT**	120	
Pseudotsuga menziesii	Douglas fir	**PM**	106	
		Total pixel:	**4775**	

1/4 of this training data is held back for evaluation (Test set)

Training Data

Species	English	Abbrevation	Pixels	Color
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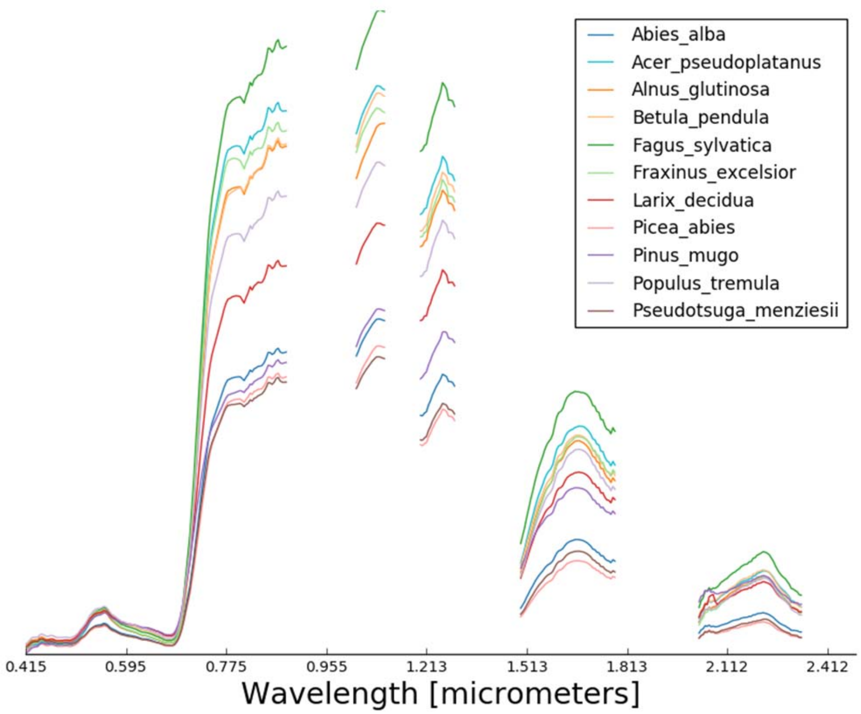
		Total pixel:	**4775**	

1/4 of this training data is held back for evaluation (Test set)

Training Data

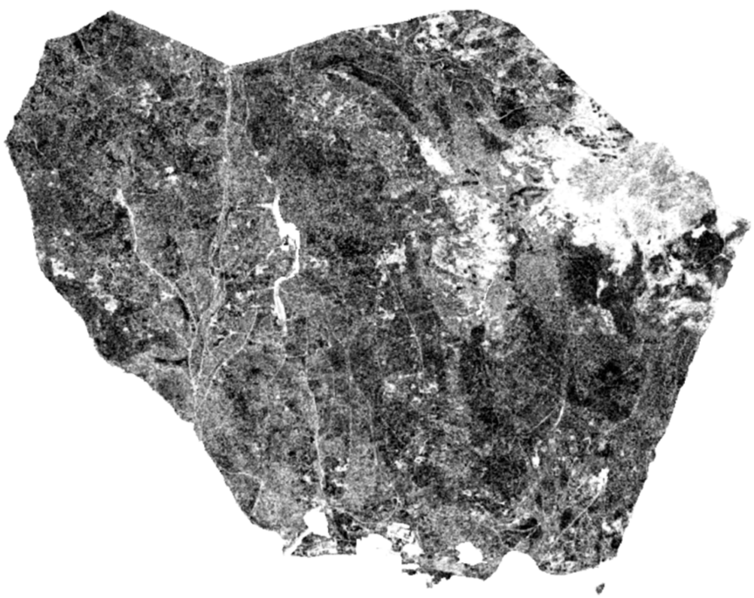
Spectral data

VNIR	SWIR	Vegetation Indices
131 Bands	133 Bands	9 Indices



LIDAR data

DTM	Treecount
Elevation	Stem density



Training Data

	Spectral			LiDAR	
	VNIR	SWIR	VI	DTM	Treecount
All	X	X	X	X	X
SpecInd	X	X	X		
Spectral	X	X			
SWIR	X				
SWIRfull		X	X	X	X
VNIR	X				
VNIRfull		X	X	X	X

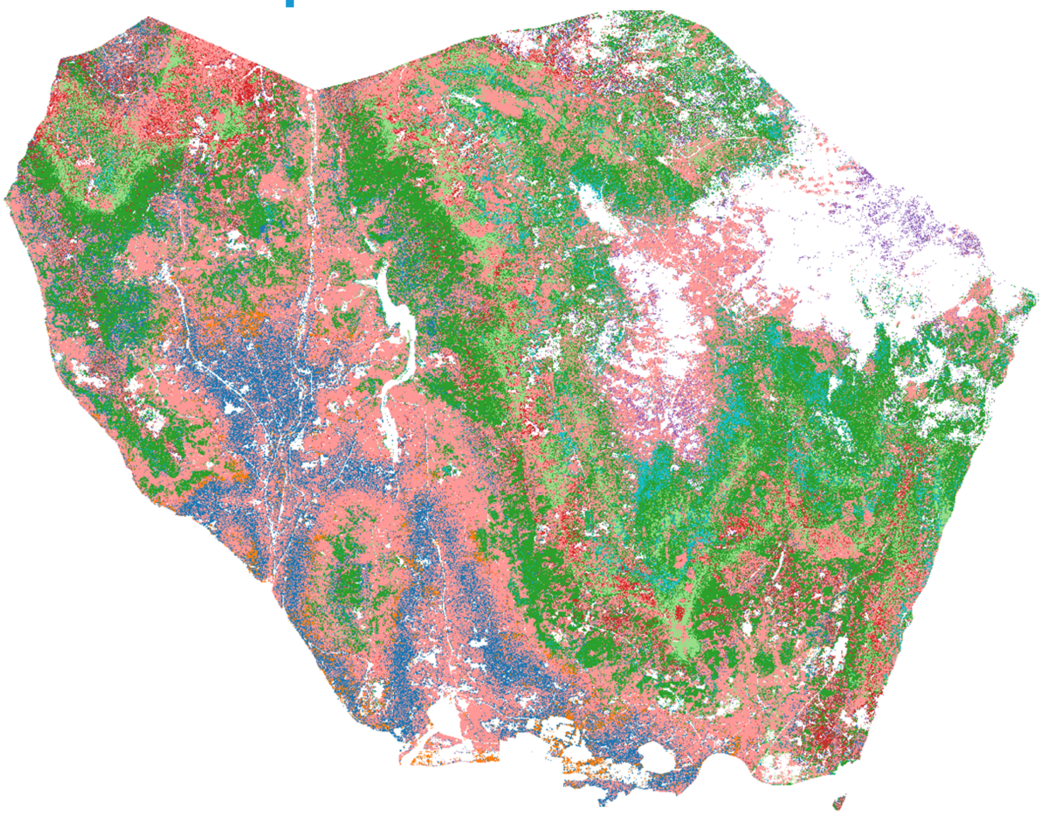
Results

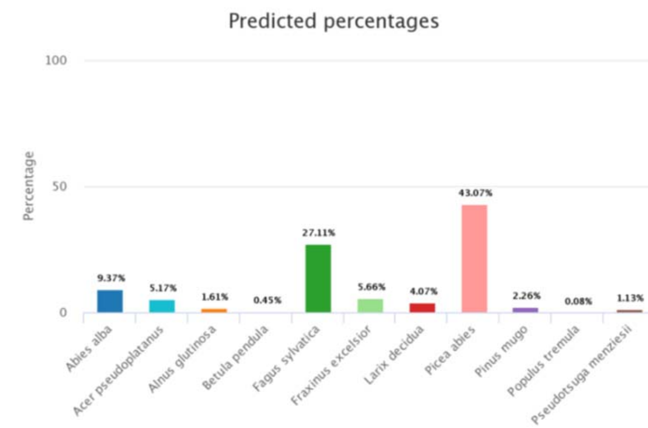
F1-Scores

Data	DTM	Kappa	AA	AP	AG	BP	FS	FE	LD	PA	PMu	PT	PM
all	True	0.77	0.67	0.74	0.82	0.75	0.90	0.82	0.81	0.77	0.95	0.67	0.55
all	False	0.64	0.55	0.56	0.58	0.60	0.86	0.69	0.67	0.73	0.86	0.31	0.07
specind	False	0.58	0.56	0.29	0.48	0.55	0.80	0.64	0.63	0.65	0.88	0.59	0.14
spectral	False	0.55	0.46	0.24	0.47	0.36	0.77	0.64	0.59	0.69	0.92	0.36	0.08
swir	False	0.53	0.52	0.32	0.36	0.23	0.74	0.69	0.52	0.71	0.82	0.06	0.00
swirfull	True	0.80	0.77	0.74	0.85	0.81	0.88	0.88	0.85	0.83	0.96	0.74	0.45
swirfull	False	0.63	0.49	0.54	0.67	0.64	0.85	0.74	0.64	0.66	0.91	0.47	0.07
vnir	False	0.46	0.37	0.27	0.44	0.29	0.76	0.48	0.53	0.52	0.86	0.28	0.07
vnirfull	True	0.77	0.71	0.82	0.82	0.74	0.90	0.81	0.80	0.76	0.95	0.72	0.65
vnirfull	False	0.62	0.47	0.55	0.56	0.65	0.83	0.65	0.63	0.70	0.88	0.53	0.19

Results

SWIR + Spectral indices + DTM + Treecount

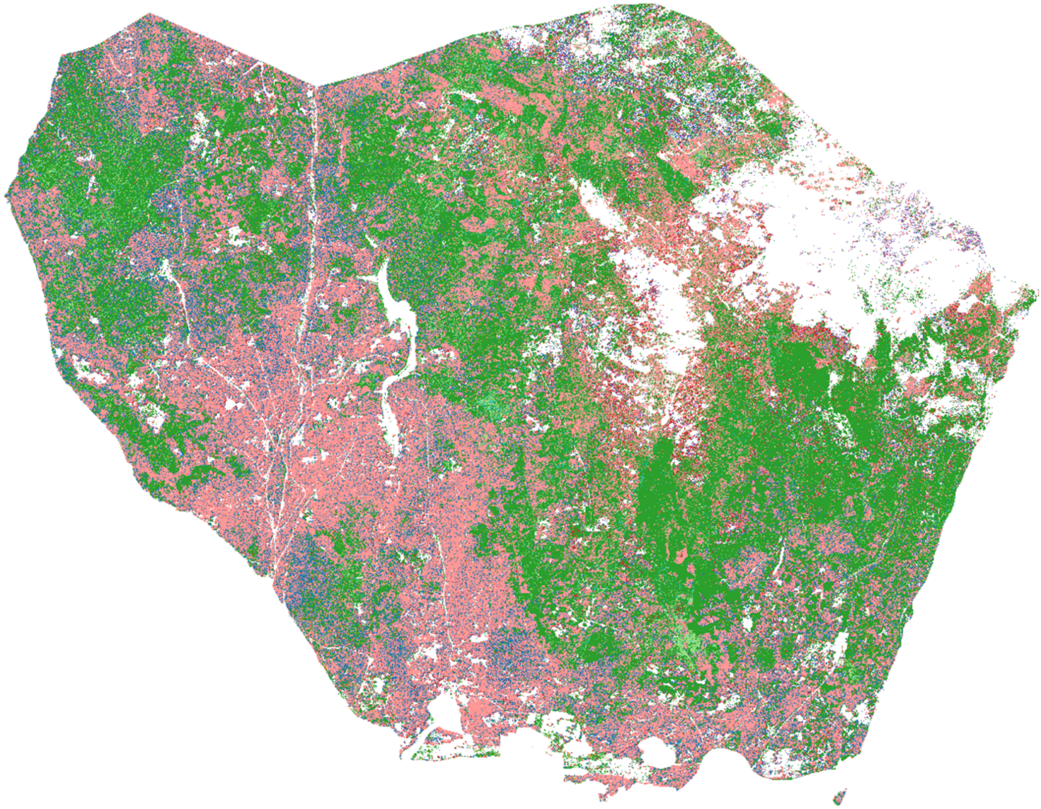


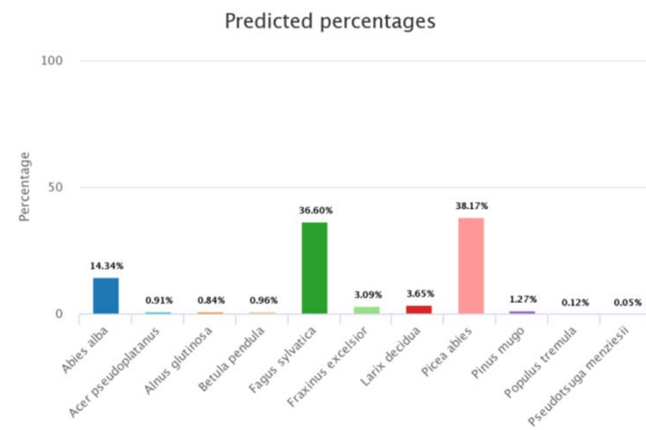


Abies alba
Acer pseudoplatanus
Alnus glutinosa
Betula pendula
Fagus sylvatica
Fraxinus excelsior
Larix decidua
Picea abies
Pinus mugo
Populus tremula
Pseudotsuga menziesii

Results

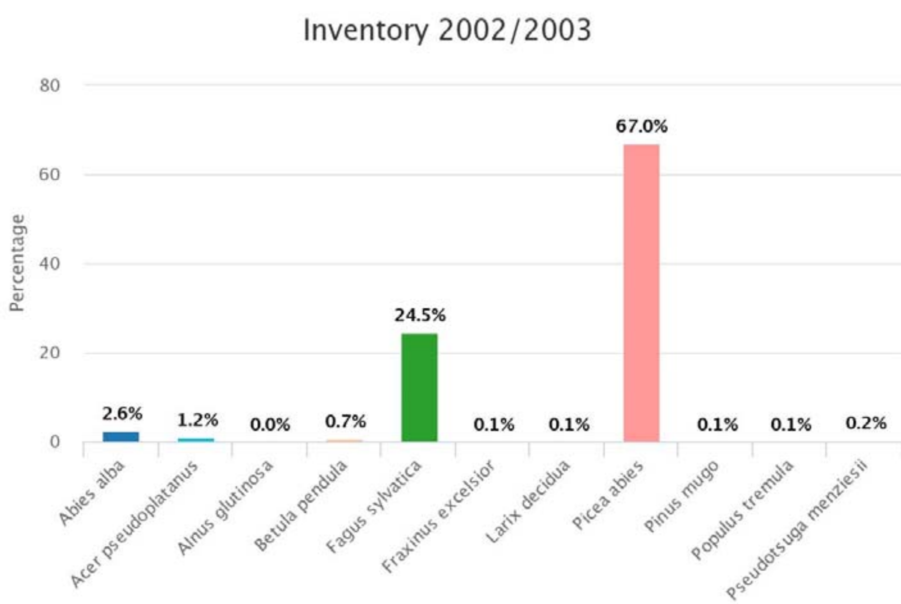
VNIR + SWIR + Spectral indices

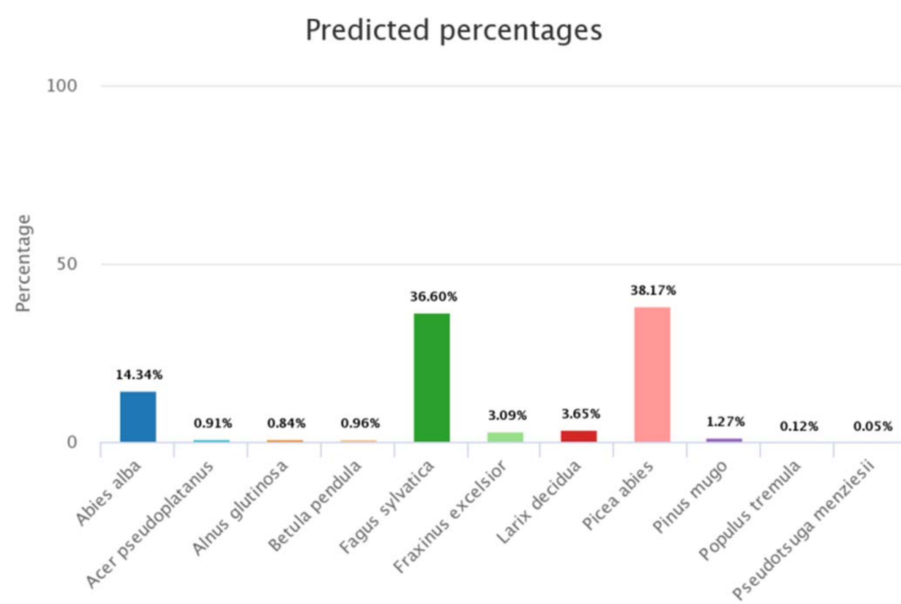




Results

Validation based on spatial distribution and overall percentages





Results
Confusion Matrix

VNIR

True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.43	0.01	0.0	0.03	0.02	0.04	0.03	0.34	0.01	0.04	0.05
AG	0.11	0.36	0.09	0.0	0.26	0.08	0.0	0.06	0.02	0.0	0.02
AP	0.09	0.05	0.11	0.03	0.09	0.58	0.0	0.04	0.0	0.0	0.0
BP	0.05	0.06	0.0	0.2	0.04	0.48	0.11	0.06	0.0	0.0	0.0
FE	0.08	0.07	0.05	0.0	0.51	0.27	0.0	0.01	0.0	0.0	0.01
FS	0.03	0.02	0.02	0.02	0.01	0.85	0.02	0.02	0.0	0.0	0.0
LD	0.16	0.0	0.0	0.01	0.0	0.11	0.55	0.12	0.0	0.04	0.0
PA	0.19	0.01	0.01	0.02	0.02	0.07	0.09	0.59	0.0	0.02	0.0
PM	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.61	0.04	0.0	0.04
PMu	0.02	0.0	0.0	0.02	0.0	0.0	0.02	0.05	0.0	0.89	0.02
PT	0.31	0.22	0.03	0.0	0.03	0.0	0.09	0.16	0.0	0.0	0.16

SWIR

True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.47	0.01	0.01	0.02	0.0	0.07	0.11	0.3	0.0	0.01	0.0
AG	0.02	0.25	0.04	0.04	0.21	0.34	0.02	0.09	0.0	0.0	0.0
AP	0.06	0.02	0.13	0.02	0.09	0.6	0.04	0.03	0.0	0.0	0.0
BP	0.04	0.02	0.0	0.27	0.05	0.49	0.09	0.01	0.0	0.0	0.02
FE	0.02	0.0	0.01	0.01	0.77	0.13	0.04	0.0	0.0	0.01	0.0
FS	0.02	0.0	0.02	0.0	0.0	0.9	0.02	0.03	0.0	0.0	0.0
LD	0.03	0.0	0.0	0.01	0.0	0.36	0.56	0.03	0.0	0.01	0.0
PA	0.2	0.0	0.01	0.01	0.0	0.04	0.02	0.72	0.0	0.01	0.0
PM	0.43	0.0	0.0	0.0	0.0	0.04	0.13	0.39	0.0	0.0	0.0
PMu	0.0	0.0	0.0	0.0	0.0	0.0	0.05	0.05	0.0	0.9	0.0
PT	0.03	0.0	0.03	0.06	0.38	0.34	0.03	0.03	0.0	0.0	0.09

Results
Confusion Matrix

VNIR+SWIR+Indices

True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.5	0.01	0.0	0.03	0.01	0.04	0.06	0.33	0.0	0.01	0.01
AG	0.11	0.6	0.09	0.0	0.09	0.04	0.0	0.04	0.0	0.0	0.02
AP	0.07	0.04	0.44	0.0	0.07	0.33	0.01	0.02	0.0	0.0	0.01
BP	0.06	0.01	0.1	0.62	0.02	0.1	0.05	0.04	0.0	0.0	0.0
FE	0.05	0.04	0.05	0.0	0.77	0.04	0.04	0.0	0.0	0.0	0.02
FS	0.03	0.01	0.02	0.01	0.02	0.87	0.02	0.02	0.0	0.0	0.0
LD	0.07	0.0	0.01	0.0	0.0	0.18	0.67	0.04	0.0	0.01	0.01
PA	0.13	0.01	0.01	0.02	0.0	0.03	0.04	0.77	0.0	0.01	0.0
PM	0.35	0.0	0.0	0.0	0.0	0.0	0.0	0.52	0.13	0.0	0.0
PMu	0.02	0.0	0.0	0.02	0.0	0.0	0.0	0.0	0.0	0.97	0.0
PT	0.31	0.12	0.0	0.0	0.12	0.0	0.09	0.03	0.0	0.0	0.31

VNIR+SWIR+Indices+Treecount+DTM

True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.61	0.02	0.0	0.02	0.01	0.04	0.02	0.21	0.01	0.01	0.02
AG	0.11	0.85	0.0	0.0	0.0	0.0	0.0	0.02	0.0	0.0	0.02
AP	0.05	0.0	0.68	0.01	0.04	0.14	0.01	0.06	0.0	0.0	0.0
BP	0.02	0.01	0.02	0.81	0.0	0.06	0.04	0.01	0.0	0.0	0.01
FE	0.02	0.0	0.0	0.01	0.9	0.04	0.01	0.01	0.0	0.0	0.0
FS	0.02	0.01	0.02	0.0	0.0	0.92	0.01	0.02	0.0	0.0	0.0
LD	0.03	0.0	0.0	0.01	0.03	0.11	0.78	0.04	0.0	0.0	0.0
PA	0.09	0.0	0.01	0.01	0.0	0.04	0.03	0.82	0.01	0.01	0.01
PM	0.17	0.0	0.0	0.0	0.0	0.0	0.04	0.48	0.3	0.0	0.0
PMu	0.0	0.0	0.0	0.0	0.0	0.0	0.02	0.0	0.0	0.98	0.0
PT	0.28	0.03	0.03	0.03	0.09	0.03	0.03	0.06	0.0	0.0	0.41

EUFAR
European Facility for Airborne Research

Results
Confusion Matrix

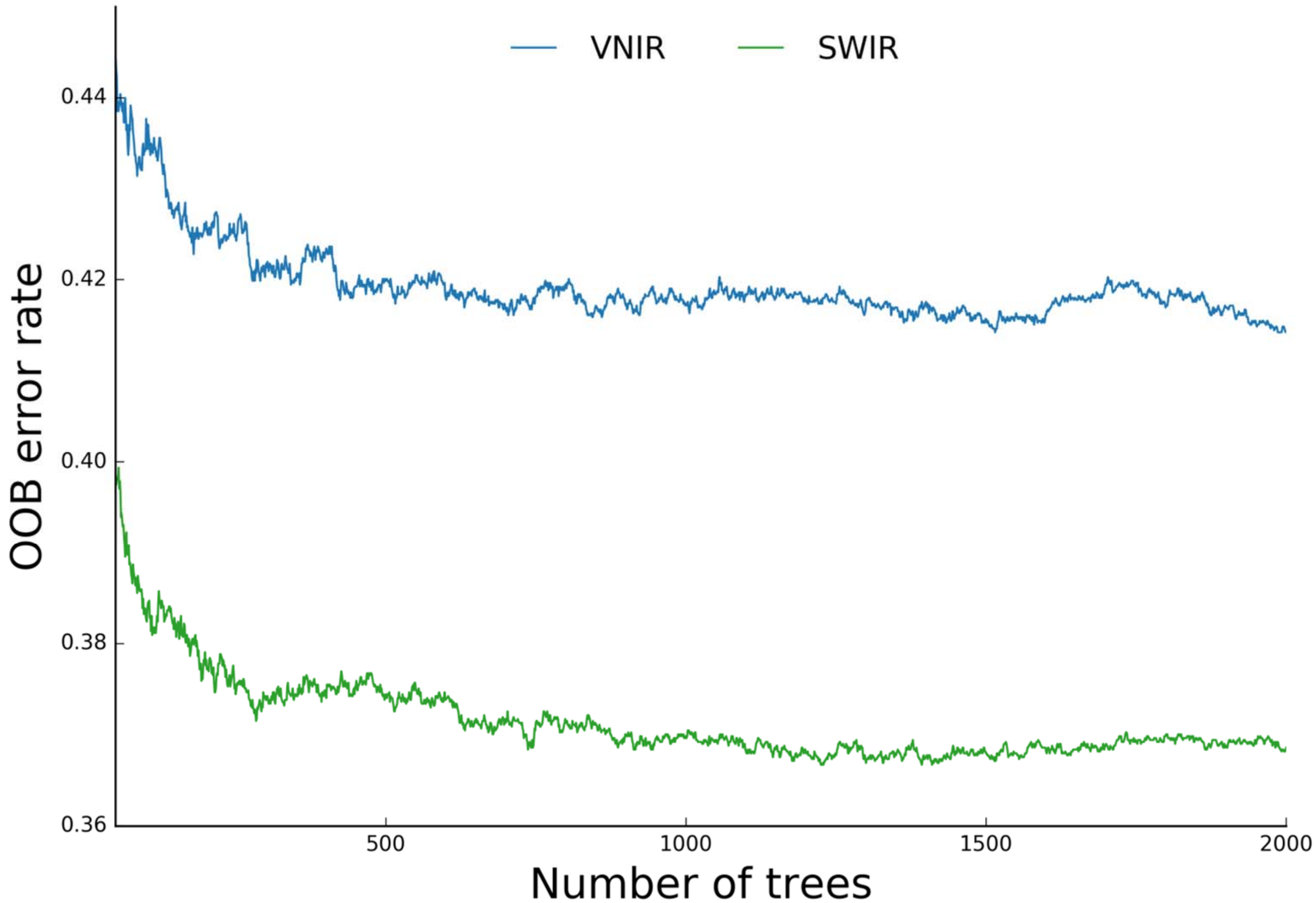
VNIR+SWIR

True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.47	0.01	0.0	0.02	0.0	0.05	0.07	0.35	0.0	0.01	0.01
AG	0.08	0.42	0.11	0.02	0.19	0.09	0.02	0.06	0.0	0.0	0.02
AP	0.05	0.04	0.13	0.0	0.06	0.66	0.01	0.03	0.0	0.0	0.01
BP	0.05	0.02	0.01	0.3	0.02	0.41	0.14	0.04	0.0	0.0	0.01
FE	0.04	0.04	0.0	0.0	0.73	0.12	0.04	0.0	0.0	0.0	0.04
FS	0.04	0.01	0.03	0.01	0.0	0.87	0.02	0.02	0.0	0.0	0.0
LD	0.05	0.0	0.0	0.03	0.0	0.18	0.64	0.04	0.0	0.03	0.03
PA	0.13	0.0	0.0	0.01	0.0	0.05	0.04	0.76	0.0	0.01	0.01
PM	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.57	0.13	0.0	0.0
PMu	0.0	0.0	0.0	0.02	0.0	0.0	0.03	0.02	0.0	0.94	0.0
PT	0.22	0.16	0.0	0.0	0.12	0.0	0.22	0.03	0.03	0.0	0.22

VNIR+SWIR+Indices

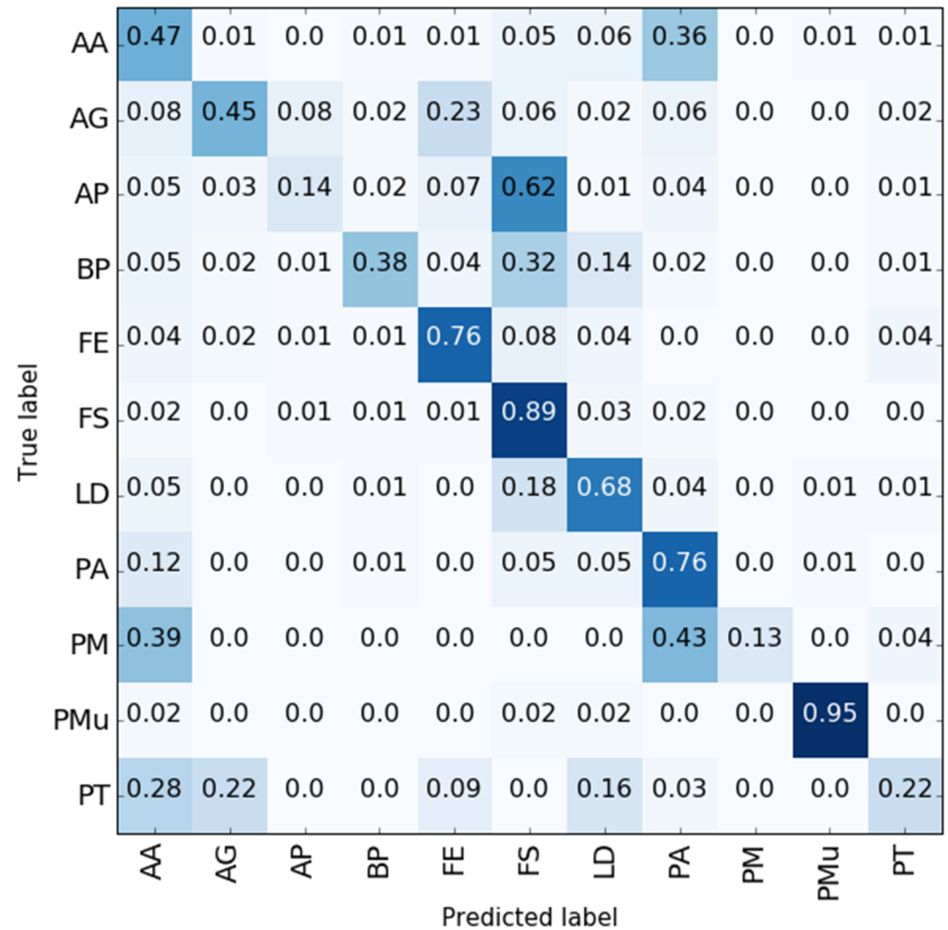
True label \ Predicted label	AA	AG	AP	BP	FE	FS	LD	PA	PM	PMu	PT
AA	0.47	0.01	0.0	0.01	0.01	0.05	0.06	0.36	0.0	0.01	0.01
AG	0.08	0.45	0.08	0.02	0.23	0.06	0.02	0.06	0.0	0.0	0.02
AP	0.05	0.03	0.14	0.02	0.07	0.62	0.01	0.04	0.0	0.0	0.01
BP	0.05	0.02	0.01	0.38	0.04	0.32	0.14	0.02	0.0	0.0	0.01
FE	0.04	0.02	0.01	0.01	0.76	0.08	0.04	0.0	0.0	0.0	0.04
FS	0.02	0.0	0.01	0.01	0.01	0.89	0.03	0.02	0.0	0.0	0.0
LD	0.05	0.0	0.0	0.01	0.0	0.18	0.68	0.04	0.0	0.01	0.01
PA	0.12	0.0	0.0	0.01	0.0	0.05	0.05	0.76	0.0	0.01	0.0
PM	0.39	0.0	0.0	0.0	0.0	0.0	0.0	0.43	0.13	0.0	0.04
PMu	0.02	0.0	0.0	0.0	0.0	0.02	0.02	0.0	0.0	0.95	0.0
PT	0.28	0.22	0.0	0.0	0.09	0.0	0.16	0.03	0.0	0.0	0.22

Results


VNIR
SWIR
0.44
0.42
0.40
0.38
0.36
OOB error rate
500
1000
1500
2000
Number of trees

Results

Spectral normalized Confusion Matrix

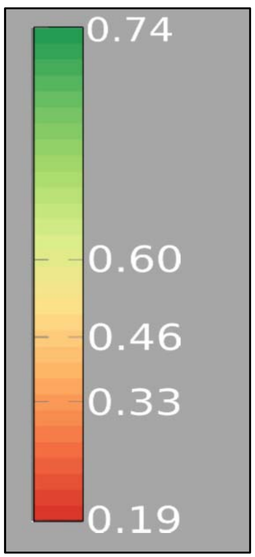


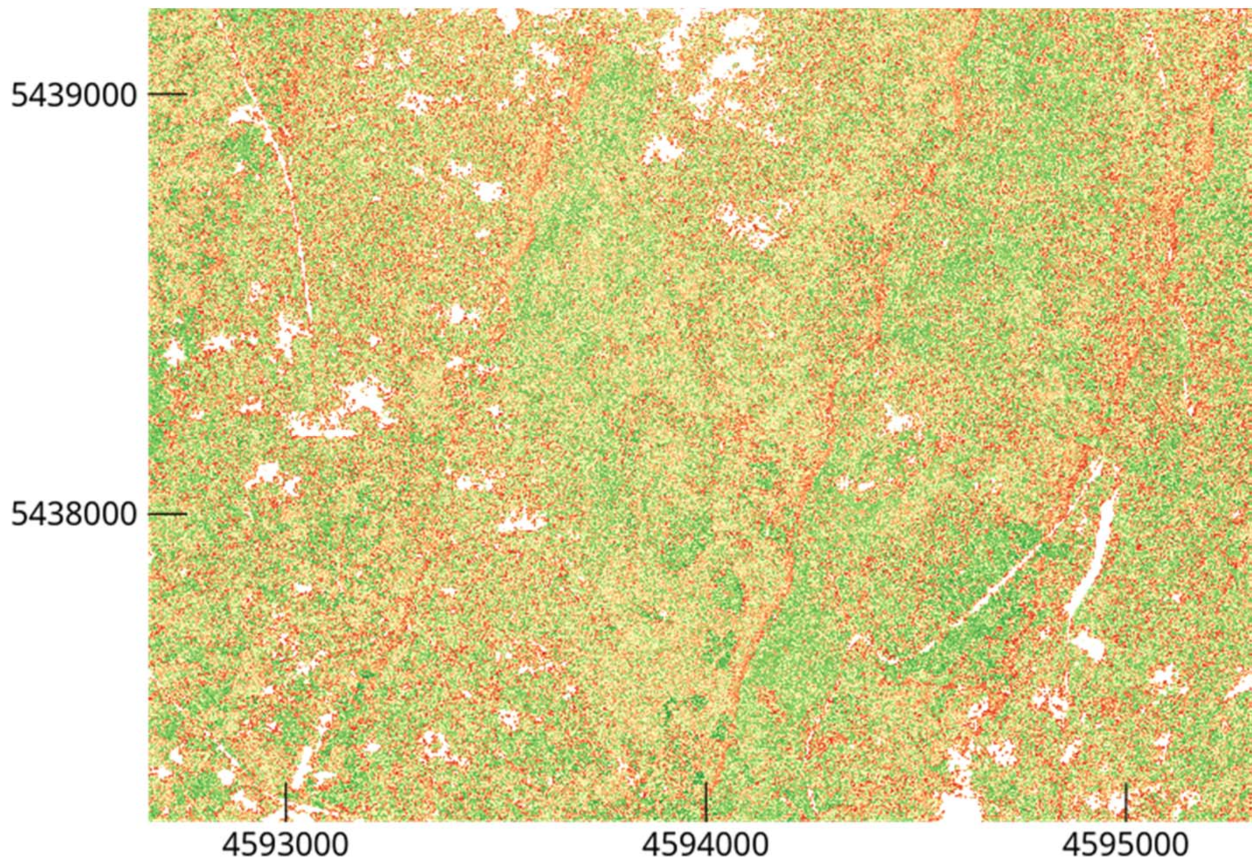
Results

Probability of predictions

Results

Probability of predictions





Conclusion I

- Full spectral coverage (VNIR-SWIR) was very useful
- Spatial resolution of 3.2 m was sufficient
- Training data sampling is difficult, especially for the minority classes
- Structural information e.g. tree count was beneficial

Conclusion II

- Development of multi-source approach for tree species classification in the Bavarian Forest National Park
- Final analysis with Random Forest revealed successful discrimination of tree species with an overall accuracy of 94%
- Application of spectral, structural, and topographic information increases the separability of species having similar spectral signatures

BUT: high classification model accuracy does not necessarily reveal the real map accuracy

Conclusion III

- Caution must be taken when integrating the elevation parameter

→ training and test data set should cover all possible terrain specific variations of the occurring tree species

- Over-representation of European larch due to the strong similarity to Norway spruce; Lowest classification accuracies for European white birch, Scots pine and European rowan

→ misclassifications due to the low number of available reference data

Outlook

- Transfer Classification algorithm to Šumava NP
- Include phenological information (multitemporal SPOT 5)
- Discriminate between dense and open stands
- Multitemporal analysis

Tree species naming conventions

Latin	**English**	**German**
Acer pseudoplatanus	Sycamore Maple	Bergahorn
Populus tremula	European Aspen	Pappel
Betula pendula	European White Birch	Weissbirke
Fagus sylvatica	European Beech	Buche
Pinus mugo	Scots Pine	Kiefer
Alnus glutinosa	European Alder	Roterle
Fraxinus excelsior	European Ash	Esche
Picea abies	Norway Spruce	Fichte
Larix decidua	European Larch	Lärche
Abies alba	European Silver Fir	Weisstanne
Pseudotsuga menziesii	Douglas Fir	Douglasie
	Sallow	Weide
	Common Rowan	Eberesche

Questions ?

Contact details

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